A supervised classification method based on logistic regression with elastic-net penalization for heat waves identification to enhance resilience planning in electrical power distribution grids

Luca Bellani, Michele Compare, Roberto Mascherona

Aramis s.r.l., Milano, Italy. E-mail: luca.bellani@aramis3d.com, michele.compare@aramis3d.com, roberto.mascherona@aramis3d.com

Bartolomeo Greco, Andrea Morotti, Luca Perfetto

UNARETI S.p.A., Milano, Italy E-mail: bartolomeo.greco@unareti.it, andrea.morotti@unareti.it, luca.perfetto@unareti.it

Gaetano Iannarelli

UNARETI S.p.A., Milano, Italy E-mail: gaetano.iannarelli@unareti.it
Department of Astronautics, Electrical and Energy Engineering, Università degli Studi La Sapienza, Roma, Italy

Alessandro Bosisio

Energy Department, Politecnico di Milano, Italy, E-mail: alessandro.bosisio@polimi.it

Enrico Zio

Aramis s.r.l., Milano, Italy
Energy Department, Politecnico di Milano, Italy. E-mail: enrico.zio@polimi.it
MINES ParisTech, PSL Research University, CRC, Sophia Antipolis, France
Eminent Scholar, Department of Nuclear Engineering, College of Engineering, Kyung Hee University, Republic of Korea

In the last years, extreme weather events, including heat waves, have caused extensive and long-lasting interruptions in the electric power distribution systems of large urban areas. According to the current Performance-Based Regulation (PBR) approaches for incentives aimed at strengthening utility performance, these interruptions have to be quantitatively measured in network resilience metrics, rather than reliability metrics. In this distinction between resilience and reliability, a clear definition of the extreme events is required. This, however, is still lacking. To address the problem, in this work we propose a method to define heat waves, which relies on logistic regression with elastic-net penalization to quantitatively associate environmental and operating conditions of the network to significant increments of its failures. The methodology is validated by application to the medium voltage distribution network of the city of Milano, Italy.

Keywords: Power Distribution System, Resilience, Logistic Regression, Heat Wave, Elastic Net

1. Introduction

Reliability metrics such as System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), Customer Average Interruption Duration Index (CAIDI), Customer Average Interruption Frequency Index (CAIFI) and others, are widely used for measuring the reliability of electrical power distribution networks and for demonstrating the capability of Distribution System Operators (DSOs) of coping with power outages that occur under relatively normal conditions of operation (Vugrin et al. (2017)). In this respect, many improvements have been done by DSOs which have progressively adopted more advanced asset management models Bosisio et al. (2019) as well as re-thought their networks in terms of substations and cable reinforcements, smart protections and Information and Communications Technology (ICT, Bosisio et al. (2019)).
In the last few years, a significant increase has been recorded for extreme natural events, such as hurricanes, heat waves, floodings. These have caused extensive and long-lasting interruptions

Proceedings of the 30th European Safety and Reliability Conference and the 15th Probabilistic Safety Assessment and Management Conference.
Edited by Piero Baraldi, Francesco Di Maio and Enrico Zio

ISBN: 981-973-0000-00-0 :: doi: 10.3850/981-973-0000-00-0_Articolo˙ESREL˙Ondate6

of power service, which must be measured and dealt with differently than with the network reliability metrics, and the protection solutions and strategies implemented for the reliability of the distribution network. Indeed, in case of extreme netural events, the network does not operate under the design conditions, but rather ”beyond design” (Zio (2007)).
To properly consider the interruptions caused in Major Event Days (MEDs, Billinton and Acharya (2006)), many national authorities, including the italian ARERA, introduced the concept of resilience into their regulatory frameworks (e.g., Ciasca et al. (2017)).
Power grid resilience refers to the ability of the network to continue operating and delivering power even when Low-Probability High-Consequence (LPHC) disruptions (e.g., extreme wheather events) occur. Then, designing and managing for resilience requires ensuring the system ability to absorb, recover, and adapt to disruptions in case of their occurrence, minimizing their consequences (Zio (2018)).
Formal definitions, metrics, and methods for analyzing and operationalizing grid resilience are currently being discussed and under development (Hosseini et al. (2016)), also considering interdependent critical infrastructures Liu et al. (2019). For example, Jamborsalamati et al. (2018) presents a framework for evaluating power grid resilience based on data of a real blackout happened in south Australia in 2016. In Luo et al. (2018), a method is proposed to evaluate the resilience of distribution networks by focusing on the impact of critical loads under extreme weather events, whereas Zare-Bahramabadi et al. (2017) presents a resilience-based framework for optimal switch placement in distribution systems. Concerning the hurricane natural hazard, a framework for evaluating the power system resilience is presented in Nateghi (2018), whereas a method to optimally allocate generation resources is proposed in Gao et al. (2017). Finally, Abdin et al. (2019) investigate the impact of extreme heat waves and drought events on the resilience of power grids fed by renewable energy systems.
Yet, at present no grid resilience definition, metric or method of evaluation have received universal recognition and acceptance (Vugrin et al. (2017)). Nonetheless, incentives are offered to DSOs by the national authorities to develop plans for increasing the resilience of their networks, according to criteria defined at national level. Whichever the national context, a clear definition of the extreme events that can determine ”beyond design” conditions is necessary for the definition of the incentives and the development of the plans, shifting the focus from reliability to resilience. However, this is still lacking.
In this work, we consider heat wave events, and propose a data-driven framework for their quantitative definition. The same issue is tackled in Zhang et al. (2019), with an unsupervised Gaussian mixture model clustering approach (Reynolds (2009); Rasmussen (2000)) applied to temperature and relative humidity data collected in Torino, Italy, over a period of 10 years. The framework proposed in Zhang et al. (2019) suffers from the following limitations:

- The unsupervised framework allows characterizing the different climate conditions, but these are not directly linked to the failures occurred, i.e., information related to the failures is not fully exploited.
- From the analysis of the results reported in Zhang et al. (2019), it emerges that the unsupervised framework is not capable of properly isolating the heat wave periods. Rather, it separates the summer period from the rest of the year: almost 35% of the yearly data is included in the cluster with large temperature and small humidity values. The proportion of days associated to large temperature values (more than one third) is too large to be a proper indicator of heat waves. It cannot be considered as an extreme event (i.e., LPHC disruption).
- It does not take into account the the loading conditions of the network, although it is known that they strongly affect the cable temperature and, thus, its failure behavior.

To move forward on these issues, we resort to supervised classification. To the best of the authors’ knowledge, the approach that we propose is different from those already available in the literature, as it systematically defines the heat wave by creating a quantitative association between failure data and environmental and operating conditions of the network.
The paper is organized as follows. In Section 2, we briefly introduce the resilience issue in the Italian context and particularly that of the city of Milano. In Section 3, we describe the heat waves and their impacts on power distribution networks. In Section 4, we frame the heat wave definition as a supervised classification problem and address it by the logistic regression algorithm. In Section 5, the presented framework is applied to the distribution network of the city of Milano, Italy. In Section 6, conclusions are drawn.

2. Context: resilience plans for the city of Milano

The resolution of the Italian authority ARERA 668/2018/R/eel ”Incentives to increase the resilience of electric distribution networks” ARERA (2018), asks DSOs to prepare a three-year plan for

increasing the resilience of their grids. This plan contains actions identified by the DSOs to limit the impact of natural hazards on their distribution networks.
The main natural hazards to be considered are:

- Heat waves and long periods of drought;
- Snowfalls of intensity such to cause the formation of ice or snow sleeves (wet snow) (Falabretti et al. (2018));
- Floodings due to intense rainfall;
- Wind storms and effects of salt pollution nearby the seaside;
- Falls of trees on overhead lines.

In this work, we consider the distribution network of Milano, which consists of about 600 Medium Voltage (MV) feeders at 23 kV and about 880'000 Low Voltage (LV) customers served by more than 6'000 MV/LV substations. This network is meshed so as to fulfill the N-1 reliability criterion: if any edge fails or is shut down, the operational layout of the network can be rapidly changed to guarantee the supply to the interrupted customers through another feeder.
In the specific case of the DSO of Milano UNARETI (2020), the main natural hazard to be considered to prepare the resilience plan is the heat waves, which are estimated to have affected 1 million people in the last 10 years. For comparison, flooding have affected "only" 70'000 customers in the same period. Moreover, in the forthcoming years climate change is expected to make heat waves more intense and more frequent than before.

3. Effect of heat waves on distribution networks

The occurrence of extremely hot weather conditions (heat waves) results in both the reduction of the heat transfer from cables to soil and the increase of power demand because of massive and simultaneous use of air conditioning. Due to thermal inertia, when these conditions last for some days, the network cables reach high temperatures (even 30°C larger than in the winter season), with consequent heavy thermal stresses causing multiple failures.
This leads the network to operate beyond the N-1 reliability design criterion, significantly challenging the network operability and possibly leading to long power outages affecting a non-negligible number of customers. For example, Figure 1 shows the case in which a multiple faults scenario causes a long interruption, because of no possibility of restoration from another feeder. We assume that the first failure occurs on vertex D, i.e., the first part of the feeder. This is in agreement with the experience that failures are more likely to occur on these parts of the grid, loaded by the whole power delivered by the feeder. In case of outage in D, the power has to come from an alternative path: the first section of the feeder from vertex B to vertex A has now to carry the whole power of the subnetwork highlighted in red. If a second failure occurs on the most loaded part of the network, i.e., close to B, all the MV/LV substations in red remain unsupplied till one of the two paths is fixed by field operators. This situation is critical in the case of underground cables because the time to find and repair the outage can last up to 12 hours.

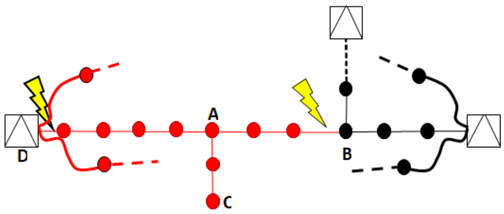

Fig. 1.: Simultaneous fault and MV/LV affected by power outage

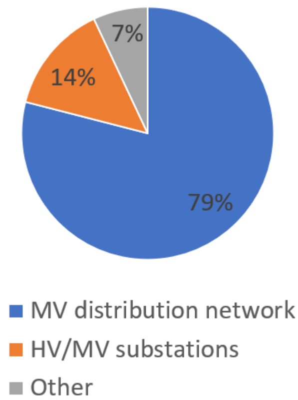

Fig. 2.: Five-year recorded failure data repartition on the distribution network of Milano, Italy

On the other hand, MV feeders are the part of the distribution network in Milano most affected by failures (Figure 2): almost 80% the recorded failures affect these edges, whereas only a few faults are experienced by HV/MV substations (e.g. short-circuit on bus-bars, triggering of transformer protection devices) or the LV distribution network.
Based on these considerations, the resilience analysis is focused on the identification of the weakest MV feeders, which in case of heat waves are likely to produce a double-failure event as that schematized in Figure 1.

4. Logistic Regression for the identification of heat waves

We consider heat waves as those periods in which the weather and operating conditions of the network are such to determine trends of failure occurrence and intensity statistically different from those of other periods, which are considered of normal failure behavior. To translate this intuitive concept into a quantitative definition, we relate the number of occurred failures to weather conditions and network loads. Specifically, we consider the following data, limited to M days of the period May-September and recorded for Y years:

- Total daily load of the electricity network. In the case of Milano, these are sampled every 15 minutes from the High Voltage - MV transformers.
- Temperature and relative humidity. For the Milano case study, these data are collected from weather stations every 10 minutes.
- Failure data. These are relevant to cables and joints, only (i.e., we do not consider substation failures, as these are typically not associated with heat waves). Yet, we consider only the failures whose causes have been ascertained to not be associated with others hazards (e.g., floods, ice hoses, etc.). We define $\phi(t)$ as the variable which counts the number of simultaneous failures at time t. In words, $\phi(t)$ can be seen as a sum of dirac's-delta functions. The data encode the timestamps of the failures.

We define the heat-wave period of S days in which more than F failures occur. $F \in [F_{min}, F_{max}]$ is the discriminating threshold to be identified for distinguishing between normal and heat weave conditions with respect to failure occurrence. The values F_{min} and F_{max} are selected by an Inter Quartile Range (IQR)-based outlier detection procedure (Schwertman et al. (2004)), setting two different thresholds (e.g., 3-rd quartile + $1.5 \cdot IQR$ and 3-rd quartile + $4 \cdot IQR$).

The samples of Y years recordings are appended one after the other, so that the complete dataset includes $D = \left\lfloor \frac{M}{S} \right\rfloor \cdot Y$ samples, where $\lfloor \square \rfloor$ denotes the integer part of $\square$. The timestamps of the S-length windows are given by Eq. 1, where $t_{s,y}$ identifies the date of the s-th sample of year $y \in \{1, ..., Y\}$, and $t_{0,y}$ is pre-fixed for all the years considered. Notice that for simplicity, in Eq. 1 we assume that $\frac{M}{S} > \left\lfloor \frac{M}{S} \right\rfloor$.

Formally, label $y_d = 1$ identifies the heat wave in the dataset as the S days corresponding to period $\mathcal{T}_d = [t_d - S, t_d]$ in which at least F failures have occurred, $d \in \{1, \ldots, D\}$; $y_d = 0$ is the label assigned to the opposite case.

To identify the conditions that define a heat wave, we extract I features from the load, temperature and humidity data, including maximum, minimum, average, standard deviation, skewness and kurtosis, each calculated on W different time windows (i.e., 3 days, 5 days, 7 days, 10 days, 15 days, 20 days,...). These feature values are arranged in vector $\mathbf{z}_d \in \mathbb{R}^{I \cdot W}$, $d \in \{1, \ldots, D\}$. We then build a classifier function $\hat{y} = f(\mathbf{z})$ mapping the generic vector of environmental and operating condition features $\mathbf{z}$, onto the indicator of heat wave occurrence.

For supervised classification, we rely on a binary logistic regression classifier with elastic-net penalties (Zou and Hastie (2005)) to automatically select the features of interest among the $I \cdot W$ considered.

In further details, the logistic regression problem reads as Eqs. 3-6. Logistic regression (Eq. 3) provides the probability for the prediction to be equal to 1, depending on the feature values. Once trained, we can set prediction $\hat{y} = 1$ if and only if $p_{\boldsymbol{\beta}}(\mathbf{z}) \geq 0.5$. This probability value can be regarded as a degree of confidence in our prediction $\hat{y}$, in this case beyond coin-flipping random prediction.

With respect to Eq. 5, we have to consider that when building a classifier of heat waves, two issues must be taken in mind:

- The two classes are unbalanced: the heat wave periods are far fewer than the normal ones, i.e. $\sum_{d=1}^{D}(1 - y_d) >> \sum_{d=1}^{D}(y_d)$. This implies that considering classificator accuracy as loss function may lead the classifier to not properly identify the class of interest $y_d = 1$.
- To be conservative, it is more important to limit the number of False Negatives (FNs, i.e., observations at $d \in \{1, \ldots, D\}$ for which $y_d = 1$ and $\hat{y}_d = 0$) than the number of False Positives (FPs, i.e., observations at $d \in \{1, \ldots, D\}$ for which $y_d = 0$ and $\hat{y}_d = 1$). Indeed, it is preferable to report the conditions in which there is a risk of an anomalous number of faults, even if it is not true that the anomalous "wave" of faults occurs, rather than not triggering alarms when environmental risk is high. This is in agreement with our definition of heat-waves: even if the considered dataset experienced multiple periods of hot environmental conditions, these do not necessarily imply large numbers of failure occurrences.

To address both issues, in Eq. 5 we impose in the training phase that the weight of the FNs error is $E = 20$ times that associated with the FP error.

$$t_d = t_{s,y} + S \qquad s = (d-1) \mod \left\lfloor \frac{M}{S} \right\rfloor, \qquad y = \left\lfloor \frac{d \cdot S}{M} \right\rfloor + 1, \qquad d = 1, ..., D \qquad (1)$$

Coefficients λ_1 and λ_2 of the ℓ_1 and ℓ_2 penalization values (Eq. 4) are chosen by $N-$ fold cross-validation combined with threshold F optimization. That is, the available dataset $\mathcal{F}$ is partitioned into N folds containing periods of equal time durations. Set $\mathcal{F}_n \subset \{1, ..., D\}$ contains the $\underline{D} = \left\lfloor \frac{M}{S} \right\rfloor$ indexes of the data in the n-th fold, $n = 1, ..., N$. We solve the N classification problems $\mathcal{C}_n$, $n = 1, ..., N$, by training the algorithm on $N-1$ folds, containing the $\overline{D} = \left\lfloor \frac{M}{S} \right\rfloor \cdot (Y-1)$ data $[\mathbf{z}_{\overline{d}}, y_{\overline{d}}]$ such that $\overline{d} \in \{1, ..., D\} \setminus \mathcal{F}_n$ and testing the accuracy of the classification on data $[\mathbf{z}_{\underline{d}}, y_{\underline{d}}]$, $\underline{d} \in \mathcal{F}_n$. The procedure is repeated on all N folds. Finally, we select the penalization parameters, the threshold F^* and $\boldsymbol{\beta}^*_n$ of the classification problem with the laregest Balanced Accuracy (BA):

$$\mathrm{BA}(\mathcal{C}_n) = \frac{\frac{\sum_{\underline{d}=1}^{\underline{D}} y_{\underline{d}} \cdot \hat{y}_{\underline{d}}}{\sum_{\underline{d}=1}^{\underline{D}} y_{\underline{d}}} + \frac{\sum_{\underline{d}=1}^{\underline{D}} (1-y_{\underline{d}}) \cdot (1-\hat{y}_{\underline{d}})}{\sum_{\underline{d}=1}^{\underline{D}} (1-y_{\underline{d}})}}{2} \qquad (2)$$

The optimized parameters $\boldsymbol{\beta}^*$ characterize the relative importance of the various features, i.e., $\beta^*_i, i \in \{1, \ldots, I \cdot W\}$ represents the contribution of feature $z_{d,i}, d \in \{1, \ldots, D\}$ to defining output $\hat{y}_d$. Notice that the penalization parameters λ_1 and λ_2 may set some coefficients to 0. This allows performing feature selection directly in the training phase: $\beta^*_i = 0$ indicates that feature $z_{d,i}$ has no significant impact on $\hat{y}_d, d \in \{1, \ldots, D\}, i \in \{1, \ldots, I \cdot W\}$.

Notice also that the optimization of F entails that the heat wave is defined by the set of environmental and operating conditions, which allows fixing a threshold on the number of failures that best distinguishes the heat wave conditions from the normal ones.

Finally, the choice of relying on logistic regression rather than on other supervised classification algorithms is twofold. On the one hand, logistic regression with penalization does not suffer from the curse of dimensionality like other algorithms (e.g., K-nearest-neighbour Johnson et al. (2002)) and generally provides good classification results and features selection when trained with a large number of features. On the other hand, unlike Support Vector Machines Schlkopf et al. (2018), Random Forests Svetnik et al. (2003), Neural Networks Nielsen (2015), it has a faster training phase and provides easy-to-interpret results for experts.

5. Results

We have considered $M = 153$ and $Y = 5$. For cross validation, $N = 5$, with each fold containing the data of the same year.

Figure 3 reports the cumulative failures over $S = 3$ days (i.e., $D = \frac{Y \cdot M}{S} = 255$) on the distribution network of Milano, together with some features selected from the $I \cdot W = 144$ features of temperature, load and relative humidity data.

For both confidentiality and visualization, features and failures have been rescaled. Thus, the y-axis is quantitatively meaningless and we can only infer the relationships among these variables. From Figure 3, we can see that there is a strong correlation between the failure data and the environmental and operating conditions, especially the maximum load over three days: the periods in 2015 and 2019 with the largest numbers of failures are in perfect correspondence with the peaks of load. There is a positive correlation between the number of failures and the load and temperature data, whereas the correlation is negative between the failures and the relative humidity; smaller values of humidity generally corresponds to fewer rainy days in the considered period.

The 10 features selected by the best setting of penalized logistic regression (i.e., leading to largest BA (Eq. 2) over the cross-validation and threshold-F possible combinations) are shown in Figure 4: the y-axis reports the coefficient β^*_i for each feature. Eight features (i.e., skewness of humidity in 10 days, standard deviation of load over $3, 5, 7$ days, standard deviation of temperature over 20 days, mean of load over $3, 5$ days and maximum load over 3 days) have a positive value of the associated coefficient, which indicates that an increase in one of these features results a larger probability of heat wave condition. The remaining two features (i.e., maximum of humidity over 7 days and skewness of temperature over 5 days) have negative coefficients, which indicates that an increase in their value decreases the probability of having a heat wave. As already pointed out, a small value of maximum relative humidity over 7 days is generally associated to a sunny week; the skewness of the temperature is an indicator of the presence of sudden steps in the temperature value. Notice that the negative coefficient sign indicates that there is a larger chance of heat wave when, in a time window, there is a small proportion of measurements with small temperature values (negative skewness). The ten features selected seem in accordance with the literature (e.g., Volodin and Yurova (2013)). With respect to Zhang et al.

$$\mathbb{P}(y=1|\mathbf{z}) = p_{\boldsymbol{\beta}}(\mathbf{z}) = \frac{1}{1+e^{-\boldsymbol{\beta}\cdot\mathbf{z}}} \tag{3}$$

$$\boldsymbol{\beta}^*_n = \underset{\boldsymbol{\beta}\in\mathbb{R}^{I\cdot W}}{\arg\min} \frac{1}{\overline{D}} \sum_{\overline{d}=1}^{\overline{D}} c(\mathbf{z}_{\overline{d}}, y_{\overline{d}}) + \frac{\lambda_1}{I\cdot W} \sum_{i=1}^{I\cdot W} |\beta_{n,i}| + \frac{\lambda_2}{2\cdot I\cdot W} \sum_{i=1}^{I\cdot W} \beta^2_{n,i} \tag{4}$$

$$c(\mathbf{z}_{\overline{d}}, y_{\overline{d}}) = -\frac{E}{E+1}\cdot y_{\overline{d}}\cdot \log(p_{\boldsymbol{\beta}}(\mathbf{z}_{\overline{d}})) - \frac{1}{E+1}\cdot(1-y_{\overline{d}})\cdot\log(1-p_{\boldsymbol{\beta}}(\mathbf{z}_{\overline{d}})) \tag{5}$$

$$y_d = 1 \quad \iff \int_{t_{d-1}}^{t_d} \phi(t)dt > F^* \tag{6}$$

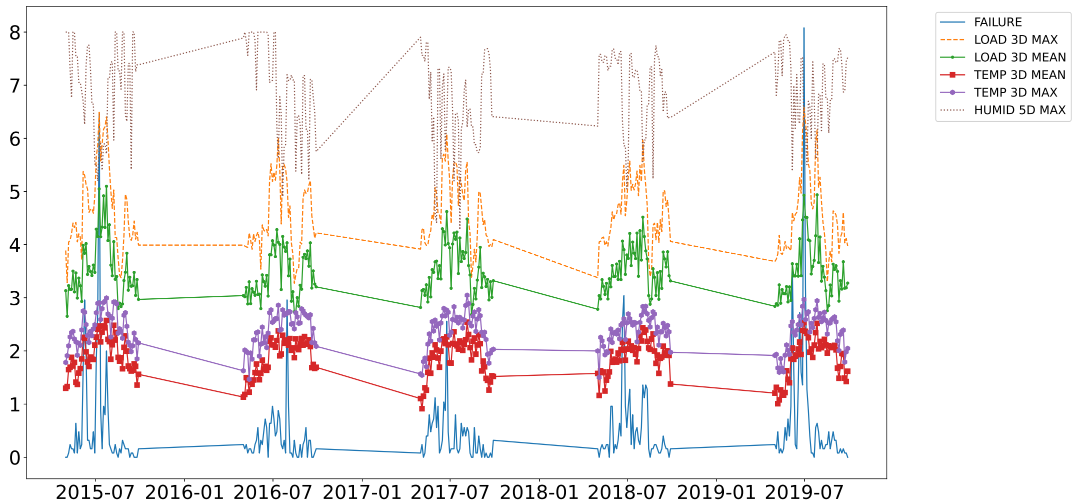

Fig. 3.: Cumulative failure over 3 days (continuous line) and some features extracted from temperature, load and humidity.

(2019), it emerges that:

- In both approaches, large temperature values and small humidity values are proper indicators of the heat conditions.
- The features related to the load, which have not been considered in Zhang et al. (2019), are those which mostly affect the number of failures (6 out of 10), as the load directly affects the thermal stress on the cables.
- Some features are not related to the absolute value of the environmental and operational conditions; rather, they are related to the presence of sudden changes (e.g., skewness of temperature) or total variation (e.g., standard deviation of load and temperature).

Finally notice that since the features have been normalized by z-score Johnson et al. (2002), the values of the coefficients can be somehow interpreted as the relative importance of the features.

The $5-$ fold cross-validation performance of the algorithm is reported in Table 1, where for each year (row) we report the total numbers of True Positives (TPs), True Negatives (TNs), FNs and FPs and the corresponding Rates $TPR = \frac{TP}{TP+FN}$, $TNR = \frac{TN}{TN+FP}$, $FNR = \frac{FN}{TP+FN}$ and $FPR = \frac{FP}{FP+TN}$ (columns), for all the $3-$day periods considered. From the analysis of the Table, we can see that there are only nine periods (sum of columns 1 and 3) in which more than F failures have been experienced (for confidentiality reasons, we cannot provide the value of F). Eigth out of these nine periods have been properly identified by the algorithm, the only exception being in year 2016, where the abnormal peak of failure does not seem related to the environmental conditions: from Figure 3, we can see that the peak of failures occurs in a period in which there is a relatively small value of the load. Despite the apparently large number of FPs (columns 3

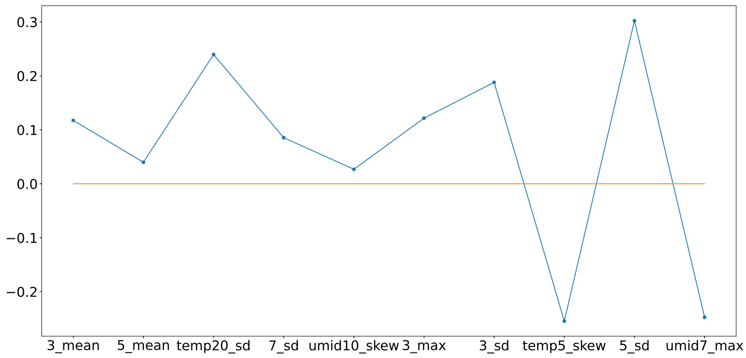

Fig. 4.: Value of the coefficient β_i^* for the 10 features selected by the elastic-net logistic regression. When we report only the time window in the x-axis, we refer to a feature extracted from the load (e.g., 3_mean stands for mean load over 3 days).

and 7), the total number of days considered by the algorithm as heat waves ($\hat{y}_d = 1$, sum of columns 1 and 3) is in accordance with the environmental conditions of Milano: years 2015 and 2019 (11 and 8 heat wave periods, respectively) have been among the hottest summers ever ARPA (2020).
Moreover, 2015 is characterized by many temperature fluctuations, which are considered risky by the skewness of temperature feature. On the other hand, 2016 has been one of the few years in the third millennium with a summer not characterized by extremely hot days ARPA (2020) and the algorithm recognized only 4 heat wave periods.
With respect to the FP metric, we can also see that in spite of the large number of heat waves identified by the algorithm in 2017 (7, column 3), there are no days with peaks of failures, although the total number of failures occurred in 2017 is far larger than that in 2016 (Figure 3). This is in agreement with the fact that the heat wave does not necessarily provide an abnormal number of failures, but only increases their probability.
Finally notice that the total number of periods with heat waves identified by the algorithm in the considered 5 years amounts to 35 (sum of columns 1 and 2), with a total of $S \cdot 35 = 105$ days of heat wave in 5 years. Very roughly, we can estimate that the average frequency of extreme hot weather events is 21 days/year.

6. Conclusions

In this work, we have proposed a method to define the heat waves bringing large risk of multiple failures that strongly challenge the resilience of the network. We have proposed a supervised classification algorithm based on logistic regression with elastic-net penalty to relate the temperature, load and humidity data to the heat wave condition. The methodology has been applied to the weather, load and failure data of the city of Milano. The good cross-validation performance has shown that the selected features properly identify the heat wave conditions. The features are easy to interpret and in accordance with the experts' knowledge. Future research work will exploit the proposed framework for a proper definition of network resilience.

References

Abdin, I., Y.-P. Fang, and E. Zio (2019). A modeling and optimization framework for power systems design with operational flexibility and resilience against extreme heat waves and drought events. *Renewable and Sustainable Energy Reviews 112*, 706–719.

ARERA (2018). Delibera ARERA - Incentivazione economica degli interventi di incremento della resilienza delle reti di distribuzione dell'energia elettrica.

ARPA (2020). Meteorological data of Milan. *https://www.arpalombardia.it*.

Billinton, R. R. and J. R. Acharya (2006). Major event day segmentation. *IEEE Transactions on Power Systems 21*(3), 1463–1464.

Bosisio, A., A. Berizzi, A. Morotti, A. Pegoiani, B. Greco, and G. Iannarelli (2019). IEC 61850-based smart automation system logic to improve reliability indices in distribution networks. *2019 AEIT International Annual Conference, AEIT 2019*.

Bosisio, A., D. Giustina, S. Fratti, A. Dede, and S. Gozzi (2019). A metamodel for multi-utilities asset management. *2019 IEEE Milan PowerTech, PowerTech 2019*.

Ciasca, F., A. Sallati, et al. (2017). Italian national resilience plan 2017: For a more reliable grid. In *2017 AEIT International Annual Conference*, pp. 1–5. IEEE.

Falabretti, D., M. Delfanti, and M. Merlo (2018). Power systems' resilience against ice sleeves: An assessment methodology tested in the smart city vizze project. In *2018 IEEE International*

Table 1.: "Confusion matrix" of the cross-validation performance of the proposed algorithm; every fold corresponds to a different year.

Year	TP	FP	FN	TN	TPR	FPR	FNR	TNR
2015	3	8	0	40	1	0.17	0	0.83
2016	0	4	1	46	0	0.08	1	0.92
2017	0	7	0	44	N.A.	0.14	N.A.	0.86
2018	1	4	0	46	1	0.08	0	0.92
2019	4	4	0	43	1	0.09	0	0.91

Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), pp. 1–6. IEEE.

Gao, H., Y. Chen, S. Mei, S. Huang, and Y. Xu (2017). Resilience-oriented pre-hurricane resource allocation in distribution systems considering electric buses. *Proceedings of the IEEE 105*(7), 1214–1233.

Hosseini, S., K. Barker, and J. E. Ramirez-Marquez (2016). A review of definitions and measures of system resilience. *Reliability Engineering & System Safety 145*, 47 – 61.

Jamborsalamati, P., M. Moghimi, M. Hossain, S. Taghizadeh, J. Lu, and G. Konstantinou (2018). A framework for evaluation of power grid resilience case study: 2016 south australian blackout. In *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*, pp. 1–6. IEEE.

Johnson, R. A., D. W. Wichern, et al. (2002). *Applied multivariate statistical analysis*, Volume 5. Prentice hall Upper Saddle River, NJ.

Liu, X., E. Ferrario, and E. Zio (2019). Identifying resilient-important elements in interdependent critical infrastructures by sensitivity analysis. *Reliability Engineering and System Safety 189*, 423–434.

Luo, D., Y. Xia, Y. Zeng, C. Li, B. Zhou, H. Yu, and Q. Wu (2018). Evaluation method of distribution network resilience focusing on critical loads. *IEEE Access 6*, 61633–61639.

Nateghi, R. (2018). Multi-dimensional infrastructure resilience modeling: an application to hurricane-prone electric power distribution systems. *IEEE Access 6*, 13478–13489.

Nielsen, M. A. (2015). *Neural networks and deep learning*, Volume 2018. Determination press San Francisco, CA.

Rasmussen, C. E. (2000). The infinite gaussian mixture model. In *Advances in neural information processing systems*, pp. 554–560.

Reynolds, D. A. (2009). Gaussian mixture models. *Encyclopedia of biometrics 741*.

Schlkopf, B., A. J. Smola, and F. Bach (2018). *Learning with kernels: support vector machines, regularization, optimization, and beyond*. the MIT Press.

Schwertman, N., M. Owens, and R. Adnan (2004). A simple more general boxplot method for identifying outliers. *Computational Statistics and Data Analysis 47*(1), 165–174.

Svetnik, V., A. Liaw, C. Tong, J. C. Culberson, R. P. Sheridan, and B. P. Feuston (2003). Random forest: a classification and regression tool for compound classification and qsar modeling. *Journal of chemical information and computer sciences 43*(6), 1947–1958.

UNARETI (2020). Piano di sviluppo e incremento resilienza. *https://www.unareti.it/unr/unareti/elettricita/cittadini/piano-di-sviluppo-e-incremento-resilienza/*.

Volodin, E. and A. Y. Yurova (2013). Summer temperature standard deviation, skewness and strong positive temperature anomalies in the present day climate and under global warming conditions. *Climate dynamics 40*(5-6), 1387–1398.

Vugrin, E. D., A. R. Castillo, and C. A. Silva-Monroy (2017). Resilience metrics for the electric power system: A performance-based approach.

Zare-Bahramabadi, M., A. Abbaspour, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie (2017). Resilience-based framework for switch placement problem in power distribution systems. *IET Generation, Transmission & Distribution 12*(5), 1223–1230.

Zhang, Y., A. Mazza, E. Bompard, E. Roggero, and G. Galofaro (2019). Data-driven feature description of heat wave effect on distribution system. In *2019 IEEE Milan PowerTech*, pp. 1–6. IEEE.

Zio, E. (2007). *An introduction to the basics of reliability and risk analysis*, Volume 13. World scientific.

Zio, E. (2018). The future of risk assessment. *Reliability Engineering and System Safety 177*, 176–190.

Zou, H. and T. Hastie (2005). Regularization and variable selection via the elastic net. *Journal of the royal statistical society: series B (statistical methodology) 67*(2), 301–320.