a possible "candidate" for MV network regulation purposes.

Residual Voltage *u* [%]	Duration *t* [ms]				
	10≤ *t* ≤200	200< *t* ≤500	500< *t* ≤1000	1000< *t* ≤5000	5000< *t* ≤60000
90 > u ≥ 80	CELL A1	CELL A2	CELL A3	CELL A4	CELL A5
80 > u ≥ 70	CELL B1	CELL B2	CELL B3	CELL B4	CELL B5
70 > u ≥ 40	CELL C1	CELL C2	CELL C3	CELL C4	CELL C5
40 > u ≥ 5	CELL D1	CELL D2	CELL D3	CELL D4	CELL D5
5 > u	CELL X1	CELL X2	CELL X3	CELL X4	CELL X5

Fig. 5. CEI EN 50160 Voltage Dips classification and thresholds for N_{2a} (dotted-orange line) and N_{3b} (continuos-red line) severe events counting indices.

QuEEN PyService computes N_{2a} and N_{3b} first of all for each *true* event in accordance with the corresponding algorithm. In fact, these indices are evaluated considering both the criteria implemented in the application, namely the 2nd harmonic and DELFI classifier.

On the other hand, the MUs during a specific period, may be out of service due to faults or maintenance. For this reason, in order to have a significant statistical analysis, it is important to define the Equivalent Measurement Point (EMP) for the selected monitoring period (typically one year). This parameter provides an evaluation of the number of measurement devices actually functioning in the selected time period and it can be computed as reported in (1):

$$EMP = \frac{\sum_{N°MU} N°\text{actual operation week}}{\sum_{N°MU} N°\text{theoretical operation week}} N°MU \qquad (1)$$

Therefore, the N_{2a} e N_{3b} indices have been computed with respect to the EMP (relative indices) providing the level of severe events in the network as the number of severe voltage dips per measurement point (N°/EMP)[3].

4. The Results

The analysis of voltage dips has been performed on 61 MUs over the last six years from the 2015 to 2020. Each voltage dip presents two validity classifications: the former performed with the QuEEN criterion and the latter with the DELFI classifier. Voltage dips occurred simultaneously with the relays trip of High Voltage (HV) line distance protections (HV origin events) have been removed from the results [4].

First of all, let us consider results concerning the QuEEN criterion: the voltage dips trends with respect to the three event types are shown in Fig. 6 and listed in percentage values in Table II: the total number of voltage dips fluctuates over the years ranging from a minimum value of 5760 events, in 2020, to a maximum value of 9136 events, in 2019. It is worth to highlight that *not defined* events are not classified events namely when 2nd harmonic component criterion fails, and its occurrence is far to be neglected.

On the other hand, the percentage ratios between the different categories are maintained: averagely, the 78% are classified as *true* events while *false* and *not defined* events represent respectively the 12% and 11% of the total number of voltage dips.

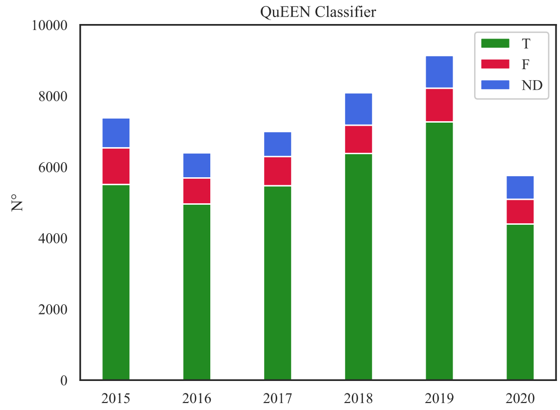

Fig. 6. Voltage dips trends from 2015 to 2020: partition into the three QuEEN criterion categories.

Table II. – Trend of QuEEN criterion events types percentages.

Categories [%]	QuEEN		
	T	*F*	*ND*
2015	74.6 %	14.0 %	11.4 %
2016	77.5 %	11.5 %	11.0 %
2017	78.2 %	11.7 %	10.1 %
2018	78.9 %	9.9 %	11.3 %
2019	79.6%	10.4 %	10.0 %
2020	76.3 %	12.1 %	11.6 %

Now let us consider, the results achieved by the DELFI classifier: the annual trends are reported in Fig. 7 while results, expressed in percentage values, are listed in Table III.

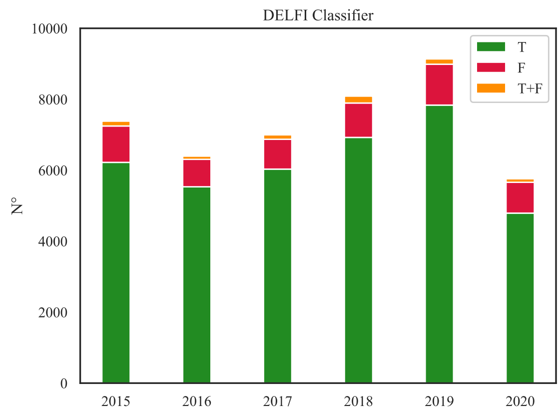

Fig. 7. Voltage dips trends from 2015 to 2020: partition into the three DELFI classifier categories.

3 The use of this parameter, rather than the number of MV bus bars monitored by the system makes the PQ analysis more precise.

4 This information has been read automatically by the QuEEN PyService from the QuEEN Database.

Table III. – Trend of DELFI classifier categories percentages.

Categories [%]	DELFI		
	T	*F*	*T+F*
2015	84.3 %	13.9 %	1.8 %
2016	86.5 %	12.1 %	1.4 %
2017	86.2 %	12.0 %	1.8 %
2018	85.6 %	12.0 %	2.4 %
2019	85.8 %	12.6 %	1.6 %
2020	83.2 %	15.1 %	1.7 %

Comparing the DELFI classifications with the QuEEN criterion ones, it can be stated that the number of detected *true* events is significantly increased reaching almost the 85% of the total number of voltage dips monitored. On the other hand, the number of *false* events remains almost the same passing from the 12% (reached by the QuEEN criterion) to nearby the 13%; moreover, the number of *true+false* event represents only the 1.8%. From these preliminary results it can be stated that the *not defined* events monitored by QuEEN are mostly classified as *true* events by the DELFI algorithm.

Now let us consider the PQ indices presented in Section 3. The N_{2a} and N_{3b} trends over the years are shown in Fig. 8 for both the classification criteria; the indices are expressed in terms of number of events per equivalent measurement point (N°/EMP).

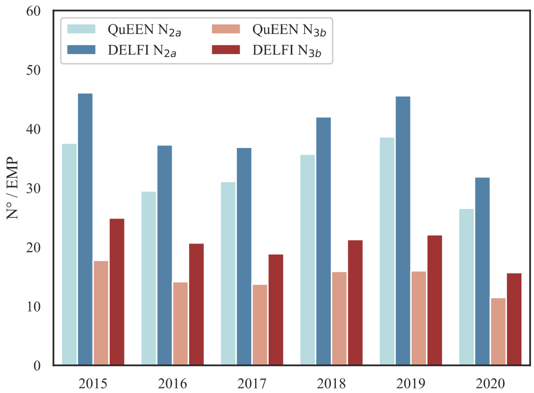

Fig. 8. N_{2a} e N_{3b} annual trends: comparison between QuEEN criterion and DELFI classifier.

By looking at the achieved results, the following conclusions can be drawn:

- referring at first to *true* events by the QuEEN criterion, N_{2a} has an average value over the considered period of 33.2 N°/EMP while N_{3b} reaches an average value of 14.8 N°/EMP;
- the application of the DELFI classifier considerably increases PQ indices: the average values for both N_{2a} and N_{3b} reach respectively 40.0 N°/EMP and 20.6 N°/EMP.

This means that a considerable number of events categorized as *not defined* or *false* by the QuEEN criterion but classified as *true* by the DELFI algorithm, significantly contributes to N_{2a} and N_{3b} evaluation.

In order to evaluate the percentage difference between the two classification methodologies, the following parameter has been defined:

$$\Delta = \frac{N_x\big|_{\text{DELFI}} - N_x\big|_{\text{QuEEN}}}{N_x\big|_{\text{QuEEN}}} \cdot 100\,\% \qquad (2)$$

where x represents the considered index. Results are reported in Table IV for each considered year together with N_{2a} e N_{3b} values.

Table IV. – N_{2a} and N_{3b} comparison: QuEEN vs. DELFI.

	N_{2a}			N_{3b}		
	QuEEN	**DELFI**	Δ [%]	***QuEEN***	**DELFI**	Δ [%]
2015	37.6	46.1	+22.7	17.8	24.9	+40.3
2016	29.5	37.3	+26.5	14.1	20.7	+46.3
2017	31.1	36.9	+18.6	13.7	18.9	+37.3
2018	35.7	42.0	+17.7	15.9	21.3	+33.9
2019	38.6	45.6	+18.0	16.0	22.1	+38.2
2020	26.6	31.9	+22.7	11.5	15.7	+40.3

By looking at the listed results, it can be noticed that there is a systematic trend: N_{2a} evaluated by the DELFI classifier is always higher, on average by 20.6%, than the same index calculated according to the QuEEN criterion, while the N_{3b} increase is equal to 38.8%. This means that a considerable number of events classified as *true* only by the DELFI algorithm contribute to both indices with a prevalent impact on N_{3b}. Therefore, the adoption of a more accurate validity classifier has a not negligible impact on the evaluation of the PQ indices N_{2a} and N_{3b}.

5. Conclusion

In this paper the development of an automated tool, called QuEEN PyService, has been presented, aimed to make advanced voltage dips analysis available in the QuEEN MV network monitoring system. First of all this application has allowed the integration of the DELFI classifier, based on Deep Learning techniques and using voltage rms sequences images as input data. The DELFI classifier is aimed to assess the validity of voltage dips and clean their statistics from voltage drops due to the measurement transformers saturation. The classifier provides always a Boolean classification (*true*, *false* and *true+false*). This allows a more accurate classification of the events respect to that achieved by the 2nd harmonic component criterion implemented in the QuEEN system, as it provides a certain number of *not defined* events.

Thanks to QuEEN PyService, the voltage dips recorded by 61 MUs between 2015 and 2020 have been considered: based on these data PQ analysis have been focused on a N_{2a} and N_{3b} more accurate evaluation. Results show that the *not defined* cases by the QuEEN criterion are mostly classified as *true* by the DELFI classifier. Those events contribute a lot to both N_{2a} and N_{3b}. As to the DELFI classifier, it boosts the above-mentioned indices respectively of the 20.6% and the 38.8% with respect to those evaluated by the QuEEN criterion.

Acknowledgement

This work has been financed by the Research Fund for the Italian Electrical System in compliance with the Decree of Minister of Economic Development April 16, 2018.

References

[1] M. H. J. Bollen et al., "Power Quality Concerns in Implementing Smart Distribution-Grid Applications," IEEE Trans. Smart Grid, vol. 8, no. 1, pp. 391-399, Jan. 2017.

[2] CIGRE/CIRED JWG C4.112, "Guidelines For Power Quality Monitoring – Measurement Locations, Processing And Presentation Of Data," TB, October 2014.

[3] http://queen.rse-web.it/

[4] IEC 61000-4-30, "Electromagnetic Compatibility (EMC)—Part 4-30: Testing and Measurement Techniques—Power Quality Measurement Methods,", 2015.

[5] CEI EN 50160, "Voltage characteristics of electricity supplied by public distribution networks,", 2010.

[6] R. Chiumeo, M. De Nigris, C.Gandolfi, L. Garbero, L. Tenti, E. Carpaneto, "Implementation of a new method for an improved voltage dip evaluation by the Italian Power Quality Monitoring System in Presence of VT Saturation Effects," in 14th International Conference on Renewable Energies and Power Quality ICREPQ'10, Granada, 2010.

[7] R. Chiumeo, C.Gandolfi, L. Garbero, L. Tenti, E. Carpaneto, "Power Quality," ISBN (10): 1-4438-9493-1, ISBN (13): 978-1-4438-9493-7, Part II, Chapter 7, pg. 102-114, Editor Mircea Ion Buzdugan, Manuel Perez Donsion, Cambridge Scholar Publishing, 2016.

[8] R. Chiumeo, H. Shadmehr, L. Tenti, "A machine learning based tool for voltage dips classification," 29th International Conference & Exhibition on Electricity Distribution, CIRED 2019, paper 0985, 2019.

[9] L. Tenti, R. Chiumeo, M. Zanoni and H. Shadmehr, "Deep Learning to Assess Voltage Dips Validity," 2020 AEIT International Annual Conference (AEIT), Catania, Italy, 2020, pp. 1-4.

[10] F. Malegori, H. Shadmehr, L.Tenti, M. Volta, F. Zanon, "Impatto sull'utente dei disturbi di PQ e automatizzazione dei metodi per la sua valutazione". RSE Report n° 17006319, Chapter 2, 2017 (in Italian).

[11] H. Shadmehr, "Analisi per la definizione di un modello di validazione dei buchi di tensione e la caratterizzazione della loro origine con tecniche di Deep Learning", RSE Report n° 19012897, 2019, (in Italian).

[12] M.D.Zeiler, R. Fergus, "Visualizing and Understanding Convolutional Networks," Course CSCI 662 Advanced, Los Angeles: University of Southern California, 2013.

[13] J. Mockus, V. Tiesis, A. Zilinskas, "The application of Bayesian methods for seeking the extremum," Towards Global Optimization, n. 2, p. 117–129, 1978.

[14] D.R.Jones, "A taxonomy of global optimization methods based on response surfaces," Journal of Global Optimization, vol. 21(4), p. 345–383, 2001.

[15] R. Chiumeo, L. Garbero, L. Tenti, C. Gandolfi, M. de Nigris, "The voltage dip performance assessment of the Italian MV network through global indices", 21st International Conference on Electricity Distribution, CIRED 2011, Frankfurt, paper 0886.

[16] CEI EN 61000-4-11 Compatibilità elettromagnetica (EMC) - Parte 4-11: Tecniche di prova e di misura - Prove d'immunità a buchi di tensione, brevi interruzioni e variazioni di tensione,» 2006.

[17] CEI EN 61000-4-34, «Compatibilità elettromagnetica (EMC) - Parte 4-34: Tecniche di prova e di misura - Prove d'immunità ai buchi di tensione e alle variazioni di tensione per le apparecchiature con corrente di ingresso superiore a 16 A per fase,» 2007.