International Journal of Innovative Computing, Information and Control
Volume **16**, Number **2**, April **2020**
ICIC International ©2020 ISSN 1349-4198
pp. 513–525

OUTLIERS TREATMENT IN POWER CURVES USING HYBRID ARTIFICIAL INTELLIGENCE TECHNIQUE

Pedro Henrique Meira de Andrade, Juan Moises Mauricio Villanueva and Helon David de Macêdo Braz

Electrical Engineering Department
Federal University of Paraíba
Cidade Universitária, 58051-900, João Pessoa, Paraíba, Brazil
{ pedro.andrade; jmauricio; helon }@cear.ufpb.br

Received August 2019; revised December 2019

Abstract. *The distribution substations power curves are often affected by outliers: very discrepant measurements of the curve standard behavior. If the presence of outliers is very large, the power utilities internal studies and analysis developed from the history of the data collected may be compromised. In order to detect and correct atypical data, a complementary module for the supervisory system was developed. In the previous work of the authors, two techniques were developed based on artificial intelligence: fuzzy logic and artificial neural networks. This work presents a hybrid technique that uses the best performances of the previous ones to reduce the relative error, increasing the correction technique performance. Furthermore, it develops an outlier detection method based on the standard behavior of the curve and the distribution of the measurements. The performances of the techniques are compared using real data from a substation over 6 years.*
Keywords: Outliers detection, Correction, Power curves, Artificial intelligence, Fuzzy logic, Neural networks, Hybrid technique

1. **Introduction.** Grids are evolving into intelligent systems, known in the literature as smart grids, and increasingly require support for network management. The Supervisory Control and Data Acquisition (SCADA) system, therefore, plays a fundamental role in the new infrastructures of the electric power systems, which require full communication with the control center of the power utilities [1].

Intelligent networks rely on sensors, actuators, real-time processing, new interfaces and new communication protocols that allow the system to introduce self-healing features with the ability to detect, analyze and correct network failures automatically [2].

The power utilities are interested in the data collected by the metering system, considering that through the historical formed analysis, maintenance and operation plans are developed, as well as the load forecast on the distribution areas. For example, a study of data history may indicate which regions are growing the most, and should be given more attention and a better allocation of resources [3].

Although the data collected by the SCADA system may be affected by outages, communication errors and instability in measurement, these occurrences can generate discrepant measured values of the load standard behavior, the outliers [4].

Therefore, in view of the importance of data history, the quality of the measurements should be sought since the data acquired are for distribution network analysis, distribution planning, outage management, load reduction and improvements in the grid. Therefore, the quality of the measured data is indispensable to not compromise the analysis. It is

DOI: 10.24507/ijicic.16.02.513

required that the dataset has a minimum integrity, i.e., a minimum amount of bad data [5].

In [6], the authors have developed a complementary module to the SCADA system to correct outliers in power curves of substations based on artificial intelligence, a technique using fuzzy logic and another one based on artificial neural networks.

In this work, a new technique is presented for the complementary module, which can further reduce forecasting errors by partitioning one-day measurements and using the best technique for each time interval. In this article, a detection technique was also developed which was not present in [6], based on the differences between the measured values and the typical values of measurement. Therefore, it is possible to identify zero and spike outliers type. The results of outliers treatment will be presented considering a feeder of a 69 kV/13.8 kV real substation located in the state of Paraba, Brazil.

The paper is structured as follows. Section 2 presents the state of art. Section 3 offers the proposed outliers treatment module showing the detection and the correction techniques focusing on the hybrid one. In Section 4 it is the analysis of the results and discussion. Lastly, Section 5 presents the work conclusions.

2. **Related Work.** The power utilities are investing in Advanced Metering Infrastructure (AMI) in which smart meters allow measurement of actual load continuously for substations, resulting in a large volume of data [7, 8].

The measurements of the electrical system meters are usually collected by the SCADA system and processed by an estimator to filter noise and detect errors. The measurements contain noise-related errors, but also erroneous data, known as bad data, in which the outliers are examples of the undesirable data [9].

The outliers treatment has been developed for several fields of applications such as engineering, economics, and meteorology. Moreover, for each application domain, a unique method according to the type of times series and the type of outlier may be developed [5, 10].

Focusing on wind farms, [11] proposed the partitioning clustering approach for outlier detection. This method consists of separating the entire range of measurements by groups using a clustering technique, k-means, calculating the centroid of each group and checking the distance of the measurements to the respective centroid of its range. An outlier processing methodology based on a wind farms probabilistic power curves and the characteristics of outliers is proposed by [5] to ensure the integrity of wind power data.

A new approach is proposed in [4] based on periodic patterns in the load curves data and a reorganization of the data to facilitate the analysis; [12] presents an analytical framework for online characterization of outliers in synchrophasor data. In [13], an outlier detection algorithm based on density of hypercube in high-dimensional data stream is proposed to increase the detection rate.

To detect and correct outliers in the electrical systems, [14, 15] proposed to use another meter, providing a metering redundancy. Nonetheless, this method is not efficient because it is more expensive, doubling the number of required meters. Furthermore, if the measurements of the two meters are different, we will be able to detect an error, but there will be an ambiguity. An architecture based on Kalman filter with outlier treatment is proposed by [16] to improve state estimation and fault detection within the power grid.

The method proposed by [17] is based on employing linear error-correcting block codes modification using to provide redundant measurements. Although the proposed method is proved theoretically, there are some practical challenges in the implementation. A Kalman filter with two stages is presented by [18] to estimate the magnitudes and phase of the voltages. In the first stage, there is the estimation of the static states, and in the second stage the estimation of the dynamic states. A different approach to outliers was used by [19] in which the focus on detecting atypical values was on the x-axis that caused a periodicity error in the electrical system data.

In [20] the focus was on the data mining generated by the SCADA system in search of outliers since the system data contains information relevant to the operation, maintenance and security, thus, improving the quality of service provided by utilities in the electricity sector. A method was developed in [21] to identify outliers based on a set of sensors in the power network signal from the probability distribution and signal strength level.

The topology of the substation studied is simple arrangement, as illustrated in Figure 1. The meters are located in the four feeders that supply cities, in this paper named as A (21L1), B (21L2), C (21L3) and D (21L4). The measured data are collected by the SCADA system every 15 minutes, with a total of 96 samples per day.

Figure 2 shows the presence of the outliers in the load curves by which it illustrates every Wednesday of the year 2010 in the 21L4 feeder that supplies the city "D". The curves present the both outliers types: zeros and spikes. When there is a problem in the transducer or there is an outage for the measurement system, there may be missing data indicating erroneously that the measurements are zero. The spike type is rarer and

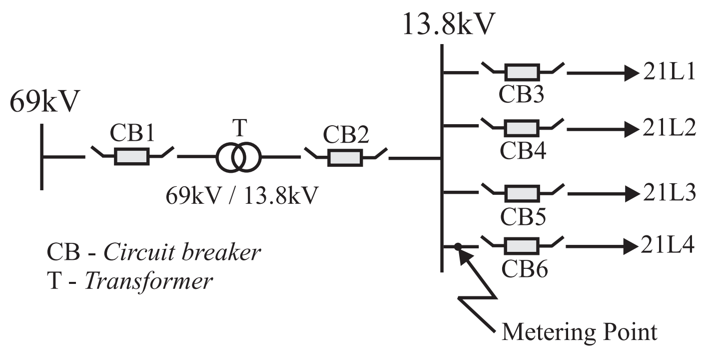

Figure 1. Substation model

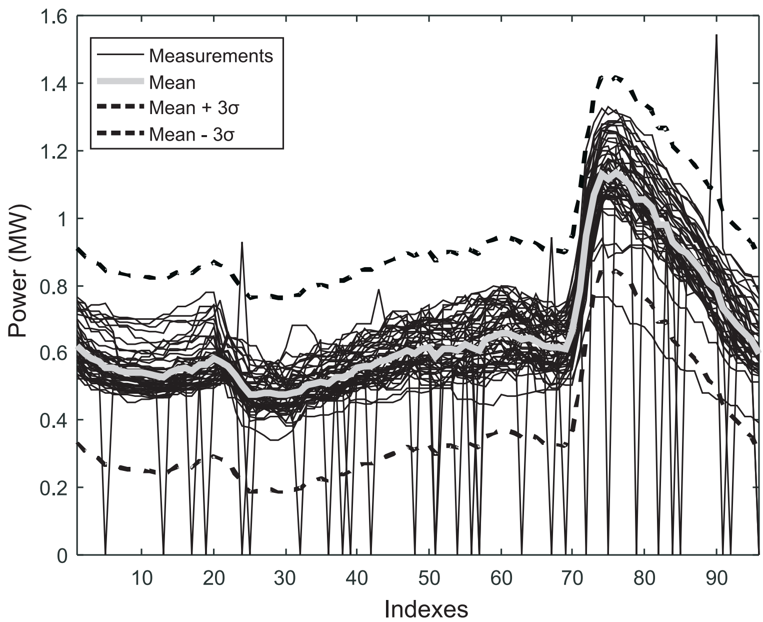

Figure 2. Curves of all the Wednesdays of the year of 2010 in the 21L4 feeder

is characterized by values with a greater magnitude than the standard behavior curve. Therefore, there is no treatment in the local power utility SCADA system that identifies and corrects erroneous measurements, compromising the data history. Thus, due to this demand, a module was developed to complement the power utility's SCADA system by detecting and correcting the outliers of the power curves. The effects analysis of outliers in load curves is evaluated, seeking for the highest possible accuracy within available information.

3. **Proposed Outliers Treatment Module.** The outliers treatment consists in both the detection of atypical values and their correction. In this work, a method was developed that detects outliers based on typical curve patterns. Outliers will be considered as zero and spike types.

According to [22], for very short-term forecasting (minutes or hours ahead) only the last measured samples should be taken into account, regardless of factors such as weather conditions and socioeconomic characteristics of the distribution area. Therefore, the proposed outliers treatment module receives a new measurement and based on the previous samples forecast the next value. The algorithm checks if the data is an atypical value. If so, this value will be discarded and replaced with the value estimated in the previous iteration. If it is not an outlier, the measured value will be considered valid and added to the historical database, as Figure 3. Thus, the technique used for outliers correction is modular, i.e., it can be replaced and the aim is to search the one with the best performance.

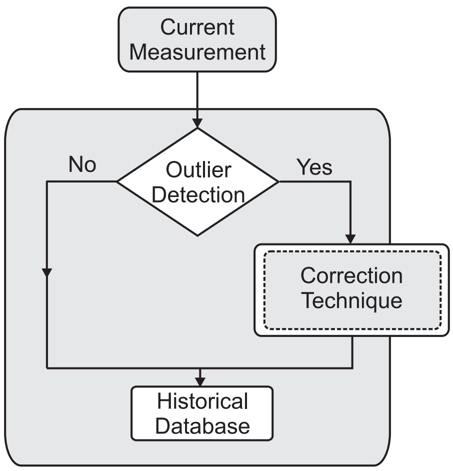

FIGURE 3. Outliers treatment module fluxogram

Outliers correction techniques have been developed and detailed in [6] and they will be compared in this work with the proposed new technique: the hybrid approach which presented the best performance. The detection and the correction techniques implemented in this article, with emphasis on the hybrid approach, using the best performances of the fuzzy technique and the ANN technique will be presented below.

3.1. **Outliers detection method.** Initially, data for the period of one year were separated according to the day of the week. That is, being 52 weeks during the year, the 52 days of Sunday with 96 measurements will be extracted for each day. Then for each day an array of dimensions 96×52 was constructed: 52 days and each day with 96 measurements. Then, the mean and standard deviation of each index were calculated. For example, for index 1, referring to time 12:00 AM, all values of 52 Sundays were summed and divided by 52. It was done this way for all indexes of the days closing with the one of number 96, referring to 11:45 PM. The curve of the means, named the typical curve, (T), was calculated for each day of the week, according to Equations (1) and (2), as well as the associated standard deviation for each day's index.

$$P_{m,n} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,n} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,n} \\ \cdots & \cdots & \cdots & \cdots \\ p_{m,1} & p_{m,2} & \cdots & p_{m,n} \end{bmatrix} \left\{ \begin{array}{l} \text{with } i \in [1, m] \therefore m = 52 \\ \text{with } j \in [1, n] \therefore n = 96 \end{array} \right. \tag{1}$$

$$T[j] = \frac{1}{m} \sum_{j=1}^{n=96} p[j] \tag{2}$$

The $P_{m,n}$ columns follow a normal distribution, checked using Jarque-Bera test [23] and Agostino-Pearson test [24, 25]. For example, $p_{i,1} \therefore i \in [1, 52]$ presents a Gaussian distribution. Therefore, for each index, the respective mean plus and minus three times the respective standard deviation is the interval with 99.73% of all samples will be within this range. Therefore, this is the detection criterion adopted.

All Fridays of the year 2010 are illustrated in Figure 4, where the gray color curve represents the mean, named the Typical Friday. The black color curves refer to the 52 Fridays of the year and the dashed curves represent the mean plus and minus three times the maximum standard deviation of the year.

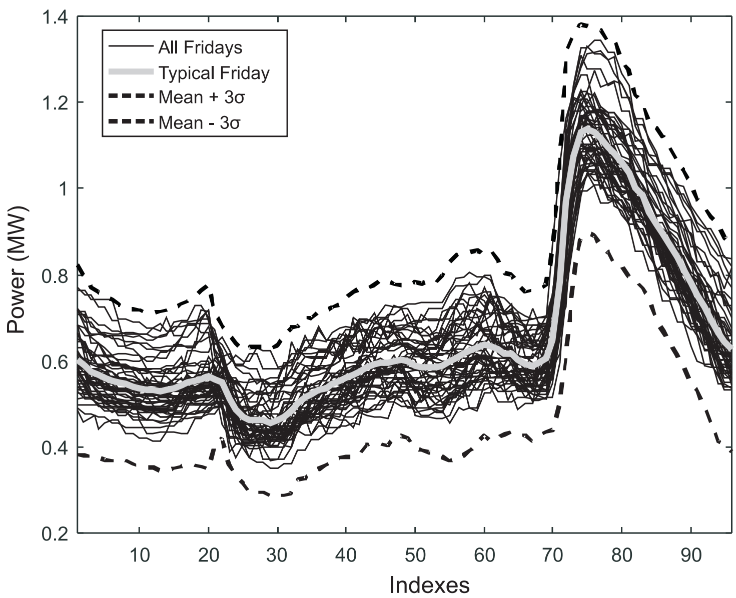

Figure 4. Measurements distribution with mean, mean plus and minus three times the standard deviation

In the detection method, with each new input value, the algorithm identifies which day of the week and which index of the day, within the range [1 : 96] equivalent to 12:00 AM to 11:45 PM. For example, if an outlier appears on a Wednesday at index 5 (1:00 AM), then the measured value will be subtracted from the index value 5 of the Typical Wednesday. If the difference (d) is greater than three times the maximum standard deviation (σ) of this year, then the measured value will be considered outlier, as shown in Algorithm 1. This method allows to detect zero and spike outliers types.

if $d \geq 3\sigma$ **then**
  $P[n] \rightarrow outlier$;
else
  $P[n] \rightarrow Valid$;
end

Algorithm 1: Outlier detection

For example, if an outlier occurs at a Monday index 13, $p[Monday, 13]$, as Equation (3), the current value will be subtracted by the index 13 of the Typical Monday, $T_{Monday}[13]$, resulting in $d(Monday, 13)$ (4):

$$p[Monday, 13] = 0 \tag{3}$$

$$d[Monday, 13] = p[Monday, 13] - T_{Monday}[13] \tag{4}$$

$$If \begin{cases} d[Monday, 13] \geq 3\sigma \therefore p[Monday, 13] \rightarrow outlier \\ d[Monday, 13] < 3\sigma \therefore p[Monday, 13] \rightarrow valid \end{cases} \tag{5}$$

3.2. **Fuzzy correction technique.** The fuzzy logic is simple to implement as long as the system behavior is known by the fuzzy expert. In the case of this work, the system is the load profiles measured by the SCADA system in the substations.

The first step is to separate the 7 days of the week in 1-year-dataset. Next, the maximum and minimum values are calculated for each day of the week for the normalization between 0 and 1:

$$P'[n] = \frac{P[n] - \min[P]}{\max[P] - \min[P]} \tag{6}$$

with $n \in [1, 35040(365 \times 96)]$, $P'[n]$ representing the normalized power value, $P[n]$ being the measured input value, $\max[P]$ and $\min[P]$ being the functions that return the values maximum and minimum of that day of the week of the sample. For example, if the current day is a Wednesday, then the respective maximum and minimum values that were separated in the first step will be considered. After normalization, the fuzzy block inputs (Figure 5) will be the differential increments calculated by

$$d_1 = P'[n-1] - P'[n-2] \tag{7}$$

$$d_2 = P'[n] - P'[n-1] \tag{8}$$

where $P'[n-1]$ is the normalized value of the immediately preceding measurement, $P'[n-2]$ is the value that precedes the previous value and $P'[n]$ is the current measurement value. The normalization is important, since the developed fuzzy inference system can be used by any other substation that has the similar power curve.

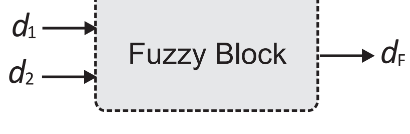

FIGURE 5. Fuzzy block with the inputs and output as differential increments

The daily behavior of the load was modeled on 25 fuzzy rules (5 sets of d_1 × 5 sets of d_2) and from the magnitudes and signs of the increments (d_1 and d_2) was determined the output of the block (d_F) which is also an incremental value and will be added to the value of $P'[n]$ to determine the estimated value:

$$P'[n+1] = P'[n] + d_F \tag{9}$$

Therefore, at each new measured value, the algorithm identifies the day of the week, normalizes the input value according to the respective maximum and minimum, and calculates the differential increments for input in the fuzzy block. The differential output increment (d_F) is added to the normalized current value, $P'[n]$, resulting in the estimated value, $P'[n+1]$. And, finally, the inverse function of Equation (6) is applied. Thus, if an atypical value appears at the next iteration, the measurement will be replaced by that calculated value.

3.3. **ANN correction technique.** The ANN correction technique is relevant because it responds significantly to the non-linear behavior of power curves. Like the fuzzy technique, it requires less mathematical-statistical knowledge about the system. Moreover, unlike the fuzzy correction, it is not necessary to know in depth the behavior of the load profiles.

Before the application of the technique on the load curves, two stages were necessary: the data treatment and the network training.

Data treatment: We randomly selected 21 days (without outliers) of the one year history with 3 representatives from each day of the week, i.e., 3 Sundays, 3 Mondays, and so on. These data were used for the construction of the input and target matrices of the neural network. The previous samples window is equal to 10 measurements; the network inputs are 10 valid measurements and the output is the forecast value, according to Figure 6. The "sliding" window was done on the database for construction of the input and target matrices that were used in the training process, as shown in Figure 7.

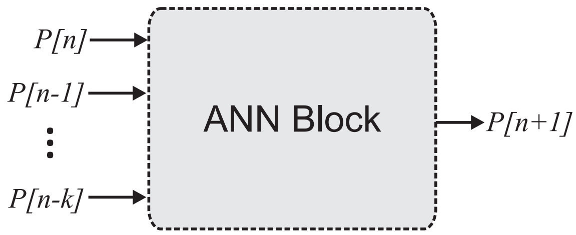

FIGURE 6. Artificial neural network for forecasting the next value. The window used was 10 samples ($k = 9$).

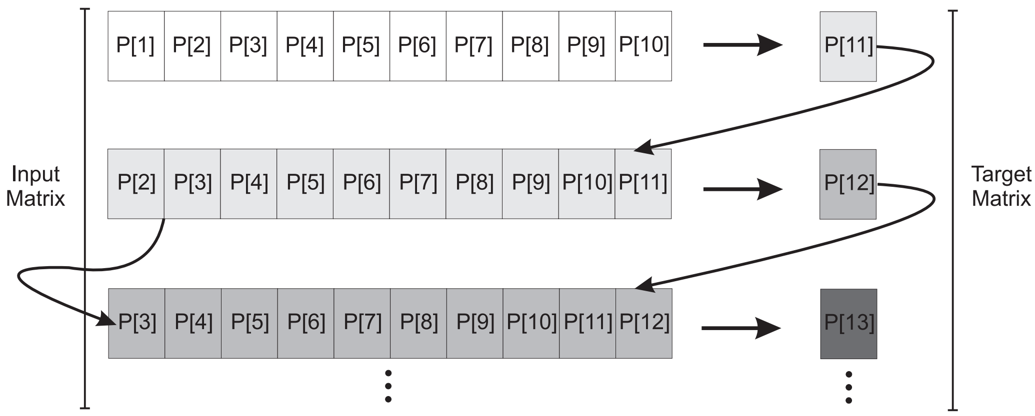

FIGURE 7. ANN matrices construction: inputs and targets

Network training: The dataset has been organized at 80% for training, 10% for validation and 10% for testing. The ANN was implemented with the input layer and one hidden layer. We have done tests with the number of nodes ranging from 1 to 10 for each layer using the Mean Square Error (MSE) as score function [26]. The best result presented 8 nodes in the input layer and 7 nodes in the hidden layer. The activation function is the hyperbolic tangent type and the Levemberg-Marquardt method was used because it is fast for small neural networks [27, 28].

3.4. **Correction hybrid technique.** It was observed after several studies on the power curves and on the correction techniques used, which were the interval of the day in which the fuzzy and ANN techniques performed better. The fuzzy correction technique has a better performance in the more constant regions of the day with the indexes belonging to the interval [1 : 20] and [41 : 64]. And when there is a greater variation in the magnitude and the signal of the derivative, i.e., at the points of greatest load variation, the ANN correction technique has a higher performance since it responds better to the non-linear behavior of the curves. The best performing interval of the ANN technique is [21 : 40] and [65 : 96], as illustrated in Table 1 and Figure 8.

Table 1. Intervals of the day and best technique associated

Interval 1	**Interval 2**	**Interval 3**	**Interval 4**
Fuzzy	ANN	Fuzzy	ANN
1 : 20	21 : 40	41 : 64	65 : 96

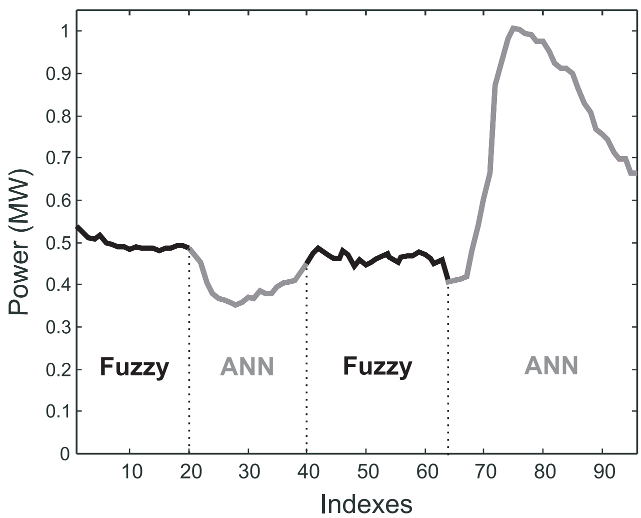

Figure 8. Intervals for the application of fuzzy and ANN correction techniques

It is important to note that the best performance in each interval is not unique and generalized to that respective technique. Although load profiles have a pattern that repeats over the years, there are often point-in-demand variations that change the curve behavior, and it may occur that the fuzzy technique performs better in the ANN interval, for example.

4. **Results and Discussion.** The results will be divided into two scenarios. The first one will have the period of 1 day; also, the advantage of the hybrid algorithm over the two other compared techniques will be detailed. The second one will test the robustness of the techniques for an interval of 6 years. The database was collected from a real substation located in the city “C”, state of Paraíba, Brazil, and corresponds to measurements on the fourth feeder (21L4), responsible for supplying the city “D”.

4.1. **First scenario: 1 day.** For the first test scenario, 4 outliers (two zeros and two spikes) were randomly inserted over the one-day curve of the feeder studied, as shown in Figure 9. Detection is illustrated in Figure 10 where the differences of the measured values and the respective typical value lie outside the region of valid measurements, identifying the simulated outliers. After the detection, the forecast is done by using the implemented correction techniques and the result generated by each technique is compared with the known real value, from the calculation of the relative errors.

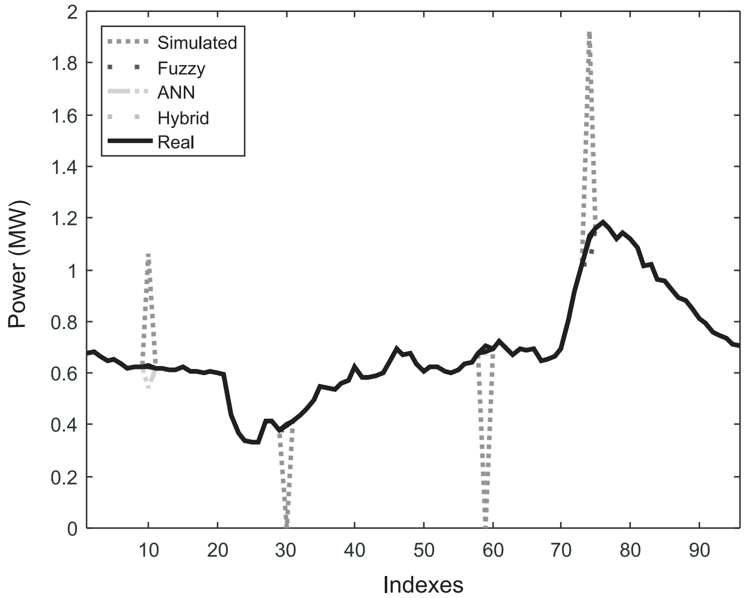

FIGURE 9. Curves of the 1-day period: simulated values and the data corrected by the developed techniques

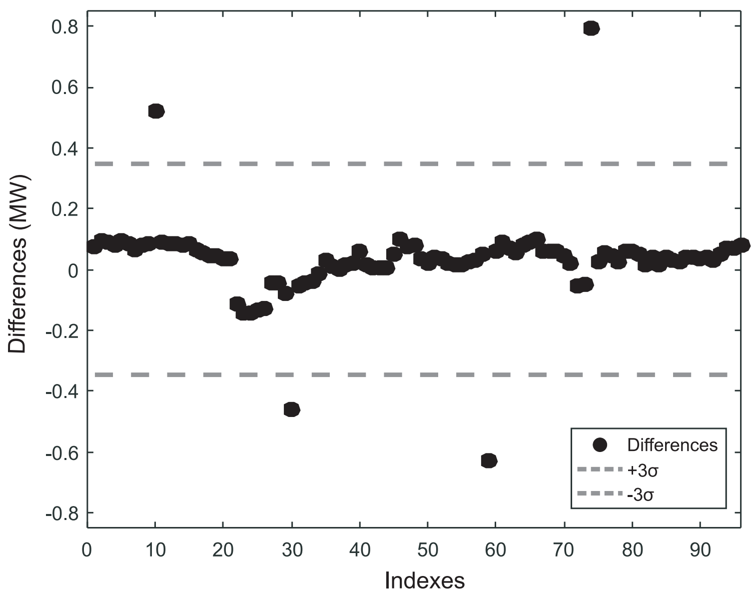

FIGURE 10. Differences and limits associated with three times the maximum standard deviation of the year

Table 2 indicates the mean of the relative errors of each developed technique. In this table, it can be seen that an outlier occurred in each interval of the day, according to Table 1. For the first interval, in which the fuzzy technique has a better performance, the relative error of this technique was lower than that of the ANN technique. Therefore, the hybrid approach error is equal to the fuzzy error. The same analysis occurs for the other three intervals where the lowest relative errors are of the ANN, fuzzy and ANN techniques, respectively. What the hybrid approach does is to take advantage of the best performance (less error) of each technique; therefore, the performance is significantly higher. In this case, the mean of the relative hybrid error is 1.67%, equivalent to less than half the mean relative error of the ANN technique which presented 4.53% and still less than the mean of the fuzzy with 4.87%. At some points it is possible that in the fuzzy interval the ANN technique performs better, although they are a minority in the general context of the load profiles.

Table 2. Relative errors for each correction technique in the 1-day-period

Index	**Relative Error Fuzzy (%)**	**Relative Error ANN (%)**	**Relative Error Hybrid (%)**
10	1.21	12.86	1.21
30	4.39	1.65	1.65
59	2.84	4.01	2.84
74	9.68	0.99	0.99
Error Mean (%)	**4.87**	**4.53**	**1.67**

4.2. **Second scenario: 6 years.** For the second test scenario, 9% of the 210432 measurements were also randomly inserted as outliers: 8% zero type (16384 erroneous samples) and 1% spike type (2104 erroneous samples). The simulated outliers were also on the 21L4 feeder.

The mean of the relative errors is indicated in Table 3 and again the hybrid approach obtained the best performance with the mean relative error equal to 4.40%. Different from the previous scenario, the difference for the ANN technique error was slightly lower, since many cases are considered as the points where the supposed best performance technique does not correspond and presents inferior performance. Figure 11 shows the curves over the 6-year period with simulated values and the data corrected by the developed techniques.

Table 3. Relative errors for each correction technique in the 6-years-period

Technique	**Fuzzy (%)**	**ANN (%)**	**Hybrid (%)**
Mean Error (%)	4.90	4.66	4.40

Another advantage of the application of the proposed outliers treatment module is the supervision of the system metering quality and integrity. It is common in the power utility that there is no metering monitoring and when the data is required for internal studies, the history is compromised with many erroneous measurements. In the analysis for the development of this work, load profiles of substations with months of missing data were studied, compromising any type of studies by the utility.

The fuzzy correction technique loses performance on slopes and sudden declines. And this scenario can be aggravated if there are too many outliers in sequence. The proposed module, after 1h30 of data absence, saves the values of the same time and day of the

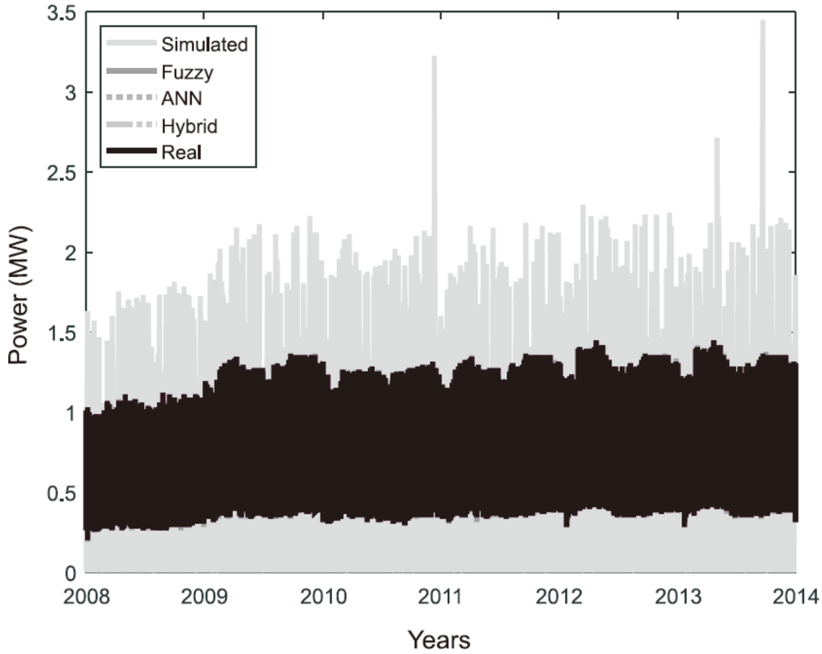

FIGURE 11. Curves of the 6-years-period: simulated values and the data corrected by the developed techniques

previous week, setting an outlier flag that the measurements being added to the data history are not provided by the metering system. From a user command, a substation report is generated informing the number of outliers for a given period in each feeder. With the knowledge of the metering systems that are defective, the power utility can generate a plan to correct the problems exposed by the proposed method. Therefore, the algorithm is used for decision making by the power utility control center for the distribution system improvement.

The power curves of the studied substations present pointwise outliers, and thus the outlier processing module developed in this article guarantees a good performance and accuracy, providing data reliability. For a large volume of outliers, other correction techniques based on the dataset history, social and economic conditions of the region should be used.

5. **Conclusion.** The outliers treatment module in the power curves combined with the SCADA system guarantees a greater reliability in the data measured in the substations. The generated database is used for internal analysis and load forecasts of medium- and long-term by power utilities, so the integrity and quality are indispensable in these studies.

In this work, an outliers detection technique and three outliers correction techniques were implemented, which were compared: fuzzy, ANN and hybrid, the latter being the one with the best performance by using the previous techniques in predetermined intervals and presenting the mean relative error to 4.40% for the scenario that considers 6 years of data.

The detection and correction techniques used are simple and do not require a high computational effort and can be used along with the SCADA system to improve the quality of the distribution substations metering systems.

REFERENCES

[1] M. Lanzrath, C. Adami, B. Joerres, G. Lubkowski, M. Joester, M. Suhrke and T. Pusch, HPEM vulnerability of smart grid substations coupling paths into typical SCADA devices, *Proc. of the 2017 International Symposium on Electromagnetic Compatibility*, 2017.

[2] X. Fang, S. Misra, G. Xue and D. Yang, Smart grid-the new and improved power grid: A survey, *IEEE Commun. Surv. Tuts.*, vol.14, no.4, pp.944-980, 2012.

[3] D. Xenias, C. J. Axon, L. Whitmarsh, P. M. Connor, N. Balta-Ozkan and A. Spence, UK smart grid development: An expert assessment of the benefits, pitfalls and functions, *Renewable Energy*, vol.81, pp.89-102, 2015.

[4] G. Tang, K. Wu, J. Lei, Z. Bi and J. Tang, From landscape to portrait: A new approach for outlier detection in load curve data, *IEEE Trans. Smart Grid*, vol.5, no.4, pp.1764-1773, 2014.

[5] Y. Xi, Z. Lu, Q. Ying, M. Yong and M. O'Malley, Identification and correction of outliers in wind farm time series power data, *IEEE Trans. Power Systems*, vol.31, pp.1-9, 2016.

[6] P. H. M. Andrade, J. M. M. Villanueva and H. D. M. Braz, Complementary module to smart meters based on outliers correction using artificial intelligence, *IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, 2018.

[7] T. Samad and M. A. Annaswamy, Controls for smart grids: Architectures and applications, *Proc. of the IEEE*, pp.1-18, 2017.

[8] W. Luan, J. Peng, M. Maras, J. Lo and B. Harapnuk, Smart meter data analytics for distribution network connectivity verification, *IEEE Trans. Smart Grid*, vol.6, no.4, pp.1964-1971, 2015.

[9] Q. Yang, J. Yang, W. Yu and N. Zhang, On a hierarchical false data injection attack on power system state estimation, *Global Telecommunications Conference (GLOBECOM 2011)*, pp.1-5, 2011.

[10] Z. Shou, H. Tian, S. Li and F. Zou, Outlier detection with enhanced angle-based outlier factor in high-dimensional data stream, *International Journal of Innovative Computing, Information and Control*, vol.14, no.5, pp.1633-1651, 2018.

[11] M. Yesilbudak, Partitional clustering-based outlier detection for power curve optimization of wind turbines, *IEEE International Conference on Renewable Energy Research and Applications (ICRERA)*, Birmingham, pp.1080-1084, 2016.

[12] K. Mahapatra, N. R. Chaudhuri, R. G. Kavasseri and S. M. Brahma, Online analytical characterization of outliers in synchrophasor measurements: A singular value perturbation viewpoint, *IEEE Trans. Power Systems*, vol.33, no.4, pp.3863-3874, 2018.

[13] Z. Shou, F. Zou, S. Li and X. Lu, Outlier detection based on density of hypercube in high-dimensional data stream, *International Journal of Innovative Computing, Information and Control*, vol.15, no.3, pp.873-889, 2019.

[14] D. P. Varodayan and G. X. Gao, Redundant metering for integrity with information-theoretic confidentiality, *Proc. of IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Gaithersburg, MD, USA, pp.345-349, 2010.

[15] M. El-Halabi, A. K. Farraj, H. D. Ly and D. Kundur, A distortion theoretic perspective for redundant metering security in a smart grid, *Proc. of the 25th IEEE Canadian Conf. Elect. Comput. Eng. (CCECE)*, Montreal, QC, Canada, pp.1-5, 2012.

[16] C. D. Sarno, A. Garofalo, G. Cerullo, N. Murru, F. D. Giandomenico and S. Chiaradonna, Power grid outlier treatment through Kalman filter, *IEEE International Symposium on Software Reliability Engineering Workshops*, Naples, pp.407-412, 2014.

[17] W. Mesbah, Securing smart electricity meters against customer attacks, *IEEE Trans. Smart Grid*, vol.9, no.1, pp.101-110, 2018.

[18] J. Zhang, G. Welch, G. Bishop and Z. Huang, A two-stage Kalman filtering approach for robust and realCtime power systems state tracking, *IEEE Trans. Sustainable Energy*, vol.5, no.2, pp.629-636, 2011.

[19] Z. Guo, W. Li, A. Lau, T. Inga-Roja and K. Wang, Detecting X-outliers in load curve data in power systems, *IEEE Trans. Power Systems*, vol.27, no.2, pp.875-884, 2012.

[20] W. Alves, D. Martins, U. Bezerra and A. Klautau, A hybrid approach for big data outlier detection from electric power SCADA system, *IEEE Latin America Transactions*, vol.15, no.1, pp.57-64, 2017.

[21] R. Rao, S. Akella and G. Guley, Power line carrier signal analysis of smart meters for outlier detection, *IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Brussels, pp.291-296, 2011.

[22] W. Charytoniuk and M. Chen, Very short-term load forecasting using artificial neural networks, *IEEE Trans. Power Systems*, vol.15, pp.263-268, 2000.

[23] C. M. Jarque and A. K. Bera, A test for normality of observations and regression residuals, *International Statistical Review*, vol.55, no.2, pp.163-172, 1987.
[24] R. B. D'Agostino, An omnibus test of normality for moderate and large sample size, *Biometrika*, vol.58, pp.341-348, 1971.
[25] R. B. D'Agostino and E. S. Pearson, Tests for departure from normality, *Biometrika*, vol.60, pp.613-622, 1973.
[26] C. Lin, H. Wang, M. Fu, J. Yuan and D. Yu, A convolution neural network based obstacle avoiding method for unmanned underwater vehicle, *ICIC Express Letters*, vol.13, no.11, pp.1079-1086, 2019.
[27] K. Levenberg, A method for the solution of certain problems in least-squares, *Quarterly Applied Mathematics*, vol.2, pp.164-168, 1944.
[28] D. Marquardt, An algorithm for least-squares estimation of nonlinear parameters, *SIAM Journal of Applied Mathematics*, vol.11, pp.431-441, 1963.