Modeling the Service Quality Indicators TIEPI and END Using Quantile Regression

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Abstract. This study investigates the continuity of electricity distribution service in mainland Portugal using quantile regression models applied to two key technical indicators: TIEPI (Time of Interruption Equivalent to Installed Power) and END (Energy Not Delivered). Based on data from E-REDES (2014–2022), the analysis evaluates how interruption frequency and duration, measured by SAIFI (System Interruption Average Frequency Index) and SAIDI (System Interruption Average Duration Index), affect energy supply resilience across different service quality zones and municipalities. Results show that SAIDI has a consistently positive and increasing effect on both END and TIEPI across quantiles, especially at the uppermost, indicating higher exposure to supply loss in the Municipality Codes with poor performance. Fixed effects highlight considerable municipal level heterogeneity, while QSR zone classifications alone do not significantly explain performance after accounting for local variation. These findings support the need for geographically target investment and regulation, and demonstrate the value of distribution sensitive modeling in infrastructure performance assessment.

Keywords: Service continuity indicators · Electricity distribution · Quantile regression

1 Introduction

The global demand for electrical energy has grown substantially in recent decades, driven by technological innovation, demographic expansion, industrialization, and increasing reliance on electronic devices. The widespread adoption of smartphones, computers, and electrified transport technologies has further intensified energy consumption, imposing considerable pressure on electricity generation and distribution systems. This presents environmental, economic, and infrastructure challenges that underscore the urgent need for sustainable energy

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solutions. Ensuring a reliable and continuous electricity supply is essential for public safety and quality of life, economic productivity, and social stability.

Whether brief or prolonged, power supply interruptions can have significant implications for individuals, businesses, and critical infrastructures, these outages result from various causes, including equipment failures (e.g., transformers, circuit breakers), adverse weather conditions, planned maintenance, network overloading, and generation issues. The impacts are widespread, ranging from financial losses and disruptions to industrial processes to risks in healthcare settings and decreased public safety due to communication and lighting systems failures.

In Portugal, the Quality of Service Regulation (QSR), administered by the Energy Services Regulatory Authority (ERSE), regulates electricity distribution service quality. This framework sets performance standards for distribution network operators, incorporating national and European guidelines tailored to the specific characteristics of the Portuguese electricity sector, [1–4]. ERSE is central in establishing annual quality targets and monitoring compliance through operators' periodic reporting. Penalties are imposed for failure to meet the defined standards, ensuring accountability and service improvement.

The QSR encourages investments in network modernization, preventive maintenance, and the adoption of advanced grid technologies to enhance resilience and consumer satisfaction. Regulatory measures address service continuity (e.g., frequency and duration of interruptions), commercial quality, and customer service standards. Outages are categorized as short (1 s to 3 min) or long (over 3 minutes), and either planned or accidental. Legal provisions such as Decree-Law No. 215-B/2012 further defines the conditions under which supply interruptions are permissible, including public interest, safety, or contractual agreement cases.

This paper uses Quantile Regression Models to present a quantitative analysis of service continuity in the Portuguese electricity distribution network, [5–7]. The objective is to identify structural differences across service quality zones and determine which factors significantly influence performance, particularly in the distribution's tails, where conventional mean-based models fall short.

The paper is structured as follows: Sect. 1 introduces the paper; Sect. 2 presents the dataset and outlines the quantile regression methodology; Sect. 3 discusses the model results for END and TIEPI, followed by a comprehensive discussion in Sect. 4; and Sect. 5 outlines conclusions and future research directions.

2 Quantile Regression Approach to Service Continuity Indicators

This study applies quantile regression analysis to investigate the determinants of service continuity performance in the Portuguese electricity distribution network, focusing on the indicators TIEPI (Time of Interruption Equivalent to Installed

Power) and END (Energy Not Delivered). These indicators are critical to evaluating the efficiency and resilience of the medium-voltage distribution system, as they directly reflect the impact of interruptions on installed capacity and energy availability. Their outcome is particularly dependent on the interruptions, both in duration (SAIDI) and number (SAIFI) and location (Municipal Code and QSR zone).

2.1 Data and Scope

The analysis is based on data provided by E-REDES, mainland Portugal's leading electricity distribution system operator, through its Open Data Portal. The dataset spans 2014 to 2022 and includes detailed records on service interruptions across all Portuguese municipalities. Indicators are disaggregated by Municipality Codes and classified according to the Quality of Service Regulation (QSR) zones:

- ▷ Zone A: District capitals or municipalities with over 25,000 customers;
- ▷ Zone B: Municipalities with 2,500 to 25,000 customers;
- ▷ Zone C: Remaining municipalities with fewer than 2,500 customers.

The Municipality Codes are 278 which spread into the 3 QSR Zones referred.

Service continuity is assessed through the standard reliability indicators:

- SAIDI (System Average Interruption Duration Index);
- SAIFI (System Average Interruption Frequency Index).

In this study, we treat TIEPI and END as dependent variables, hypothesizing that they are functions of both interruption patterns (SAIDI and SAIFI) and contextual variables, including geographic classification, as Municipality Codes, and also considering different zones of Quality of Service Regulation (QSR).

2.2 Methodology

To analyze the determinants of these service continuity indicators, we implement quantile regression models, [8,9] which allow for the estimation of covariate effects across different points of the conditional distribution of the response variable. Unlike ordinary least squares (OLS), which models the mean of the dependent variable, quantile regression is robust to outliers and reveals heterogeneity in predictor effects across quantiles. These seem more appropriate for analyzing performance in both high and low reliability municipalities exhibiting non-homogeneous variability.

The quantile regression model is formally specified as:

$$Q_{Y_i}(\tau \mid X_i) = \sum_{j=1}^{k} \beta_j(\tau) X_{ij}, \tag{1}$$

where $Q_{Y_i}(\tau \mid X_i)$ is the τ-th quantile of the response variable (TIEPI or END) conditional on the covariates X_i, and $\beta_j(\tau)$ are the quantile-specific regression coefficients. The presented model excludes the constant to be in accordance with the interest variables in study.

2.3 Model Specification

The models for TIEPI and END include the following predictors:

- SAIDI and SAIFI: Continuous variables measuring the average duration and frequency per customer;
- QSR Zone: Categorical variable (zone A, zone B, and zone C) representing the regulatory zone classification;
- Municipality Code: Fixed effects to control for unobserved heterogeneity at the local level.

The models were estimated for multiple quantiles (e.g. $\tau = 0.25\,,\ 0.50\,,\ 0.75$) to capture differences between municipalities with low, median, and high levels of interruption severity.

2.4 Analytical Objectives

This study applies the proposed quantile regression framework to assess the heterogeneity in the continuity of the electricity service in municipalities on mainland Portugal. We are interested in analyzing the influence of interruption indicators such as the System Average Interruption Duration Index (SAIDI) and SAIFI (System Average Interruption Frequency Index) on the distribution of TIEPI and END. The goal is to determine whether and which Municipality Codes experience frequent or more extended outages and are disproportionately more vulnerable regarding installed capacity and not delivered energy. In addition, to evaluate whether the classification of Municipality Codes under the Quality of Service Regulation (QSR) Zones remain significant predictor of performance.

3 Results

This section presents the results of the quantile regression analysis, which TEIPI and END variables as functions of average interruption duration (SAIDI), QSR Zone classification, and Municipality Codes. The model was estimated at three quantiles: the 25th, 50th (median), and 75th percentiles, to capture variation across the distribution of TEIPI and END values and better understand performance drivers under different service continuity levels.

3.1 Descriptives

The descriptive statistics are presented below only for TIEPI, END and SAIDI medium voltage (mv) in Table 1, [10,11]. It turned out that the number of interruptions, despite being an important indicator, did not have a significant impact on the TEIPI and END variables.

Table 1. TIEPI, END and SAIDI medium voltage (mv) – QSR Zone—descriptive statistics.

	QSRZone	N	Mean	Median	SD	Min.	Max.
TEIPI	Zone A	2502	4.01	0.0	16.96	0	423.18
	Zone B	2502	24.67	0.41	42.69	0	493.53
	Zone C	2502	83.71	67.18	72.31	0	885.27
END	Zone A	2502	1.61	0.0	8.39	0	136.87
	Zone B	2502	3.29	0.01	8.42	0	95.56
	Zone C	2502	8.15	5.33	8.83	0	104.22
SAIDI	Zone A	2502	4.52	0.0	819.33	0	423.18
	Zone B	2502	27.86	0.68	46.17	0	602.26
	Zone C	2502	96.11	76.61	81.41	0	748.40

In the descriptive analysis, it was pointed out that the effect of QSR Zones is not significant in TEIPI and END results. Although the same variables result reveals key differences concerning the Municipality Codes, as can be observed in the graphical representations, Fig. 1, in which the line regression of the variables across the Municipality Codes is plotted.

3.2 Model Fit

Results for TEIPI. Variable TIEPI (Time of Interruption Equivalent to Installed Power) was modeled as a dependent variable using quantile regression. The explanatory variables included SAIDI, QSR Zones classification, and Municipality Codes. The model was estimated at the 25th, 50th, and 75th percentiles to capture variation in system vulnerability.

The pseudo R-squared values for the TIEPI model were:

- 0.737 at the 25th percentile,
- 0.834 at the 50th percentile,
- 0.875 at the 75th percentile.

These results suggest improved model performance at higher quantiles, indicating that greater variability in TIEPI can be explained among Municipality Codes with poorer continuity results. The Mean Absolute Error (MAE) are 7.62 (25th), 6.16 (50th), and 7.38 (75th), similar for the considered quantiles.

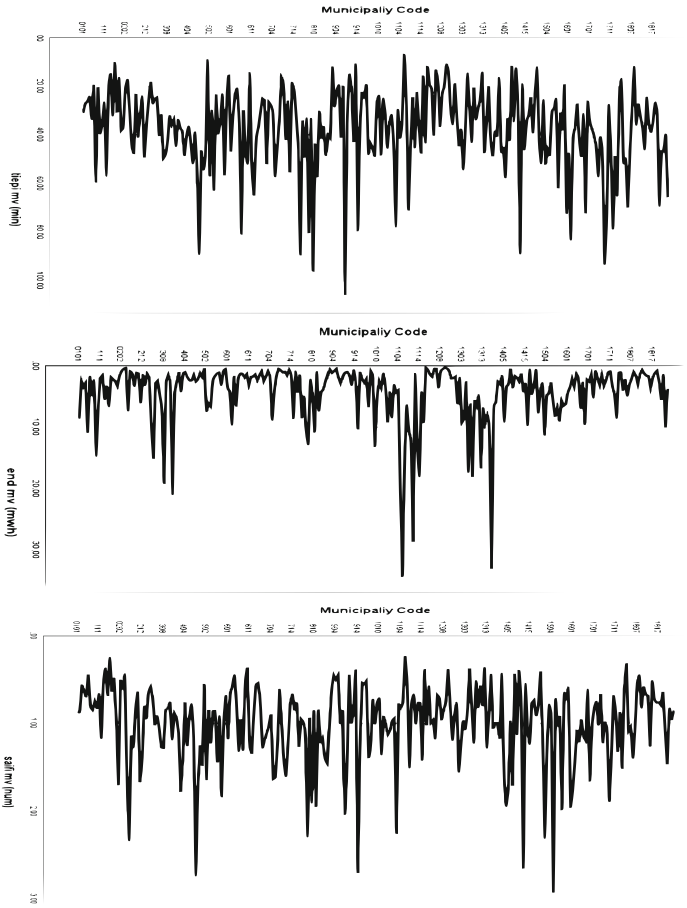

Fig. 1. Three vertically aligned X-Y charts display data trends across different municipality codes. Each chart has a horizontal axis labeled "Municipality Code". The vertical axes represent different measurements: the top chart shows "TEIPI mv (mm)," the middle chart "END mv (mwh)," and the bottom chart "SAIDI mv (num)." The data lines fluctuate significantly across all charts, indicating variability in measurements across municipalities.

Effect of SAIDI

The variable SAIDI (System Average Interruption Duration Index) had a positive and statistically significant effect on TIEPI across all quantiles, increasing as the quantiles increase:

- $\beta = 0.767$ at the 25th percentile,
- $\beta = 0.879$ at the 50th percentile,
- $\beta = 0.984$ at the 75th percentile.

This finding indicates that longer average interruption durations lead to higher capacity weighted exposure, which is more pronounced among the worst-performing Municipality Codes.

Municipality Codes Effects

Municipality Codes fixed effects revealed considerable variation in TIEPI outcomes. It was observed that several Municipality Codes show high coefficients, particularly for 75th quantile, ($q = 0.75$):

- Municipality Code 107: coefficient = 3.907 ($q = 0.75$),
- Municipality Code 314: coefficient = 3.146 ($q = 0.75$),
- Municipality Code 1301: coefficient = 3.905 ($q = 0.75$),
- Municipality Code 1503: coefficient = 4.485 ($q = 0.75$),

With respect quantiles $q = 0.25$ and $q = 0.5$ the coefficients present low values, thus no referring critical locations.

These findings point to localized structural deficiencies, operational stress, or environmental vulnerabilities affecting system reliability. Figure 2, below, presents Time of Interruption Equivalent to Installed Power (TEIPI) values across municipalities for the 25th, 50th, and 75th quantiles are presented. The vertical axis represents TEIPI, and the horizontal axis denotes the Municipality Codes. Prediction lines correspond to estimated conditional quantiles from the regression model

QSR Zone Effects

The QSR Zone effects were constrained due to colinearity with Municipality Codes specific effects. This outcome suggests that localized characteristics explain most of the variance in TIEPI, and that QSR zones classification alone is insufficient to differentiate performance.

Results for END: Model diagnostics indicate an increasing explanatory power across quantiles. The pseudo R-squared values were:

- 0.219 at the 25th percentile,
- 0.376 at the 50th percentile,
- 0.534 at the 75th percentile.

These results suggest that the model performs better at higher quantiles, capturing more variation in END among Municipality Codes with poorer service continuity. The mean absolute error (MAE) are 3.19 (25th), 2.71 (50th), and 3.79 (75th), similar for the considered quantiles.

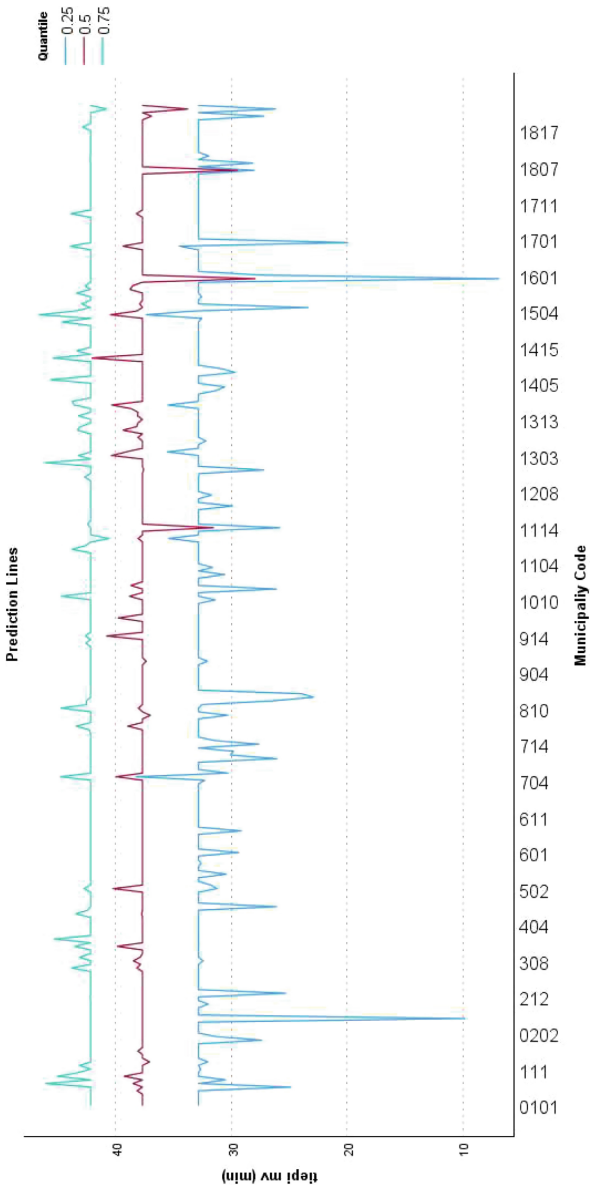

Fig. 2. Predicted TEIPI values across Municipality Codes for the 25th, 50th, and 75th quantiles.

Effect of SAIDI

The variable SAIDI (minutes) had a consistently positive and statistically significant effect across all quantiles, with increasing magnitude:

- $\beta = 0.029$ at the 25th percentile,
- $\beta = 0.046$ at the 50th percentile,
- $\beta = 0.068$ at the 75th percentile.

These results confirm that longer average outage durations are associated with higher volumes of non supplied energy, and this relationship becomes more pronounced in municipalities already experiencing greater service disruption.

Municipality Codes Effects

The fixed effects of Municipality Codes show considerable variation in their contribution to the END. Several municipalities exhibit markedly higher coefficients in the 75th percentile, suggesting structural vulnerabilities or repeated exposure to extreme outages. Several municipalities exhibited particularly high coefficients at the 75th percentile, suggesting chronic network stress or environmental vulnerability:

- Municipality Code 1306: coefficient $= 36.173$ $(q = 0.75)$,
- Municipality Code 1312: coefficient $= 40.486$ $(q = 0.75)$,
- Municipality Code 1106: coefficient $= 83.230$ $(q = 0.75)$.

Figure 3, below, presents the non-supplied energy (END) values across Municipality Codes for the 25th, 50th, and 75th quantiles are presented. The vertical axis represents END, and the horizontal axis denotes the Municipality Codes. Prediction lines correspond to estimated conditional quantiles from the regression model. Municipality Codes show considerable variation in predicted END values, particularly at the 75th percentile, where peaks are significantly higher. This indicates that a small number of Municipality Codes experience disproportionately large energy losses, confirming the presence of local performance asymmetries. The 25th and 50th percentile lines remain relatively stable across most Municipality Codes.

QSR Zone Effects

The effects of QSR Zone classifications were set to zero in the model due to collinearity, likely resulting from including detailed municipality-level fixed effects. This suggests that QSR zone membership does not independently explain variation in END once local heterogeneity is accounted for.

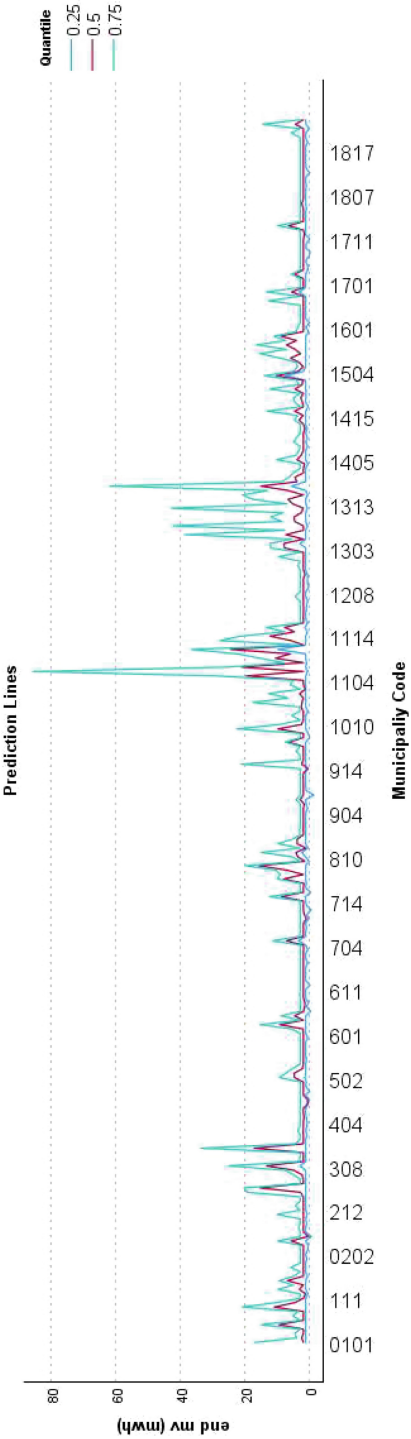

Fig. 3. Predicted END values across Municipality Codes for the 25th, 50th, and 75th quantiles.

4 Discussion

Including TIEPI in the quantile regression analysis offers complementary insight into system resilience under conditions of service interruption. TIEPI, representing the duration of supply loss relative to installed power, reflects the capacity weighted exposure of the network and its users. The strong positive association between SAIDI and TIEPI–especially at the upper quantiles–further confirms that duration of outages is a key driver of systemic vulnerability.

As with END, the variation in municipality-level effects across quantiles suggests that a few locations bear a disproportionate burden of service unreliability. This finding calls for geographically granular regulation, potentially informed by cluster analysis or machine learning-based risk profiling.

Moreover, the parallel behavior of END and TIEPI indicates that the same underlying drivers (network age, design, maintenance regime, or environmental exposure) may jointly affect both energy loss and system-level outage duration. Cross-validating the two indicators across municipalities could strengthen infrastructure prioritization frameworks.

5 Conclusion

Following the work presented in [12–14] in this study, the authors applied quantile regression to model service continuity indicators, focusing on two critical performance indicators: TIEPI (Time of Interruption Equivalent to Installed Power) and END (Energy Not Delivered), in the Portuguese electricity distribution system, similarly to [8,9]. Using data over a decade, the dataset disaggregated by Municipality Codes and QSR Zone, the results demonstrate that the duration of interruptions (SAIDI) significantly and increasingly impacts TIEPI and END as we move to higher quantiles. This implies that Municipality Codes experiencing poor service continuity are more vulnerable to additional disruptions.

The analysis also reveals that Municipality Codes effects explain most of the variability, while QSR zone classifications lose explanatory power once local heterogeneity is included. These findings suggest that infrastructure investments and regulatory oversight should be geographically targeted to address systemic vulnerability.

These findings carry significant implications for regulatory policy and investment prioritization. National distribution strategies should adopt a more geographically robust approach, identifying and targeting municipalities with persistent underperformance. Regulatory frameworks may also benefit from integrating quantile regression to evaluate performance targets that recognize and address extremes.

Future research could extend this model by incorporating dynamic factors such as environmental risk, climate exposure, and population density to provide deeper insights into the systemic drivers of energy resilience and inform infrastructure planning. In addition, a possible approach may be to develop faster algorithms based on [15] to contribute to better performance.

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References

1. Regulação da Energia — Legislação Essencial. Entidade Reguladora dos Serviços Energéticos (2024)
2. 4th Benchmarking Report on Quality of Electricity Supply 2008. Council of European Energy Regulators ASBL (2008)
3. 7th Benchmarking Report on the Quality of Electricity and Gas Supply. Council of European Energy regulators (CEER) and the Energy Community Regulatory Board (ECRB) (2022)
4. Towards Voltage Quality Regulation in Europe – an ERGER conclusions paper. European Regulators' Group for Electricity and Gas (2007)
5. Uche, E., Das, N., Cifuentes-Faura, J., et al.: Globalization, remittances, and income inequality: a novel multivariate quantile-on-quantile regression (M-QQR) perspective for top receiving countries. J. Knowl. Econ. (2025). https://doi.org/10.1007/s13132-025-02738-1
6. Čížek, P.: Quantile Regression. In: XploRe – Application Guide. Springer, Heidelberg (2000). https://doi.org/10.1007/978-3-642-57292-0_1
7. Xiao, Z.: Time series quantile regressions. In: Rao, T.S., Rao, S.S., Rao, C.R. (eds.) Handbook of Statistics, vol. 30, pp. 213–257 (2012). https://doi.org/10.1016/B978-0-444-53858-1.00009-0
8. Hammoudeh, S., Khoung, D., Sousa, R.M.: Energy prices and CO2 emission allowance prices: a quantile regression approach. Energy Policy **70**, 201–206 (2014)
9. Xu, M.: Quantile regression model and its application research. Acad. J. Sci. Technol. **8**(3) (2023). https://doi.org/10.54097/vt1qpm59
10. Morgado, L., Teodoro, M.F., Perdocoulis, T.: Manual de Métodos Estatísticos em Ciências. Universidade de Trás os Montes e Alto Douro (UTAD, Vila Real). Série Didáctica Ciências Aplicadas, 400 (2010). ISBN 978-972-669-018-2
11. Seltman, H.J.: Experimental Design and Analysis. https://www.stat.cmu.edu/~hseltman/309/Book/Book.pdf. Accessed 05 May 2025
12. Andrade, M.A.P., Teodoro, M.F.: Portuguese service electricity continuity indicators: municipality code and quality service zones evaluation – 2014 to 2022. In: Gervasi, O., Murgante, B., Garau, C., Taniar, D., Rocha, A.M.A.C., Faginas Lago, M.N. (eds.) Computational Science and Its Applications – ICCSA 2024 Workshops. ICCSA 2024. LNCS, vol. 14816. Springer, Cham (2024). https://doi.org/10.1007/978-3-031-65223-3_11
13. Andrade, M.A., Teodoro, M.F.: Portuguese service electricity continuity indicators: quality of service evaluation. In: Golubitsky, M., Lacarbonara, W., Pinto, C.M.A. (eds.) To appear in: Mathematical Analysis and Applications in Science and Engineering: ICMASC 2024, Porto, Portugal
14. Andrade, M.A., Teodoro, M.F.: Service Electricity Quality Evaluation – a cluster approach. To appear in AIP Proceedings
15. Chernozhukov, V., Fernández-Val, I., Melly, B.: Fast algorithms for the quantile regression process. Empir. Econ. **62**, 7–33 (2022). https://doi.org/10.1007/s00181-020-01898-0