Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

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This paper proposes a time-series stochastic socioeconomic model for analyzing the impact of the pandemic on the regulated distribution electricity market. The proposed methodology combines the optimized tariff model (socioeconomic market model) and the random walk concept (risk assessment technique) to ensure robustness/accuracy. The model enables both a past and future analysis of the impact of the pandemic, which is essential to prepare regulatory agencies beforehand and allow enough time for the development of efficient public policies. By applying it to six Brazilian concession areas, results demonstrate that consumers have been/will be heavily affected in general, mainly due to the high electricity tariffs that took place with the pandemic, overcoming the natural trend of the market. In contrast, the model demonstrates that the pandemic did not/will not significantly harm power distribution companies in general, mainly due to the loan granted by the regulator agency, named COVID-account. Socioeconomic welfare losses averaging 500 (MR$/month) are estimated for the equivalent concession area, i.e., the sum of the six analyzed concession areas. Furthermore, this paper proposes a stochastic optimization problem to mitigate the impact of the pandemic on the electricity market over time, considering the interests of consumers, power distribution companies, and the government. Results demonstrate that it is successful as the tariffs provided by the algorithm compensate for the reduction in demand while increasing the socioeconomic welfare of the market.
According to [6], the COVID-19 pandemic transformed electricity demand in two different ways: temporary changes and longer-term changes, which are not expected to cease completely after the pandemic. Therefore, studies of the impact of the pandemic on the electric sector are extremely important to better understand the problem and to propose mitigation measures/public policies. Efforts on assessing/planning the post-COVID-19 era are also of utmost importance and must take into account the lessons learned from the pandemic.

Several countries/regions have implemented public policies to mitigate the impact of the pandemic on electricity consumers [7], e.g., Afghanistan – waived energy bills; Bhutan – deferred electricity charges payment for industry; Eastern Caribbean – provided discounts on energy bills. In Brazil, the government implemented a policy called COVID-account in June / 2020 [8] to decrease tariff raises that occur annually by the regulatory agency. The government/regulatory agency understanding is that tariffs would increase severely due to the pandemic; thus, an intervention was required. However, further assessment of the Brazilian electricity market is essential since the policy introduced an interest rate that is likely to affect consumers in the long-term.

1.2. Literature review

1.2.1. COVID-19 pandemic, energy system, and climate governance in the post-COVID-19 era

Costa et al. [9] is the background research of this paper. The authors sought to assess the impact of the COVID-19 pandemic on the Brazilian distribution electricity market by applying the optimized tariff (TAROT) model in a time-independent/deterministic context. This paper proposes substantial approach modifications and improvements concerning Ref. [9] by introducing a time-dependent/stochastic model to assess the impact of the pandemic. A more in-depth analysis of the progress of this paper regarding Ref. [9] is carried out in the novelty and contributions section (Section 1.3).

Several high impact publications that are well inserted into the context of the COVID-19 pandemic, energy system, or climate governance in the post-COVID-19 era are described below (publications are separated by topic for an improved organization):

**Power sector in general:** Ref. [10] assesses the European power sector (focus on Germany) on a range of topics based on data visualization and descriptive statistics. More specifically, the analysis focuses on electricity consumption, generation, prices, imports/exports, grid stability, and ancillary services. Results demonstrate that the pandemic has significantly influenced electricity consumption, generation, prices, and imports/exports, unlike grid stability and ancillary services. Ref. [11] also assesses the European power sector but focuses on the effects of governmental restrictions on electrical load, generation, and transmission. Results demonstrate that generation sources shifted significantly, favoring renewables and fossil gas instead of coal and nuclear. Furthermore, energy imports/exports increased in Europe to help balance changes caused by the pandemic. Ref. [12] differs from [10,11] as it addresses the USA power sector. The analyzed topics include power system security, generation, demand, and electricity prices. The main findings are that both demand and prices have significantly dropped, and the impact varies notably geographically.

**Energy demand:** Ref. [13] applies a convolutional neural network (CNN) model to forecast oil price, production, consumption, and inventory in the context of the pandemic based on social media information. Ref. [13] is a pioneer on the topic of the relationship between social media and the oil market. Overall, 42,795 news headlines were collected as input data, and the research indicates that price, production, and consumption are influenced by social media, unlike inventory. Oil issues in the context of the pandemic are further analyzed in Ref. [14]. Ref. [15] also addresses energy demand, focusing on a worldwide holistic perspective. The general conclusion is that the total demand decreases; however, variations are complicated. Furthermore, energy recovery (which takes place when lockdown measures are relaxed) exhibits heterogeneous characteristics depending on the region. Lastly, Ref. [15] discusses challenges and emerging opportunities, providing valuable insights. Energy demand is further assessed in Ref. [16] along with utilities’ socioeconomic and technical (e.g., power quality) issues. Moreover, Ref. [16] assesses India’s context in extensive detail, providing a novel perspective related to its issues and challenges. A set of recommendations is also provided in Ref. [16] to assist the fight against the pandemic and future crises. It is emphasized that although Ref. [16] addresses socioeconomic issues, it does not focus on future simulations; hence, the work emphasis is different from this paper’s also alleviating socioeconomic issues with the context of the pandemic and its influences. Ref. [17] investigated the variation at the geographic block level in water and electricity consumption in Doha, Qatar. The study portrayed that there is a positive relationship between water and electricity consumption and that the lockout phase has a strong positive correlation between water and electricity consumption in the residential sector due to the extra water and electricity footprint in this sector. Energy demand is also the emphasis of Ref. [18], where electricity demand forecast models are developed. Such models are extremely useful in the context of atypical events such as the pandemic and can be used to enhance energy security, grid resilience, and planning. Again, energy demand is the focus of Ref. [19], where an in-depth assessment of energy demand (electricity, hot water, and space heating) is conducted for residential buildings in Canada based on real measurements in a 40-dwelling social housing. The assessment is conducted by comparing data before and after lockdown measures were implemented. The major conclusion is that consumption patterns changed due to lockdown measures, with most of the consumption being concentrated during the day. Ref. [20] also addresses energy demand issues, analyzing the impact of the pandemic in a new district design in Sweden. Ref. [20] demonstrates that electricity demand increased due to the confinement (in the study’s location); however, energy demand remained virtually the same due to other energy forms. Lastly, Ref. [21] uses smart meter data from Spain to thoroughly evaluate the pandemic’s impact on electricity demand. The proposed approach is based on automatic clustering. Such an approach proved to be essential since different groups were found to behave differently in the face of the pandemic. Overall, residential customers increased their consumption, whereas other consumption classes decreased their consumption substantially. While energy demand issues are analyzed in [13,15,16,18-21], the authors analyze different locations and apply different methods; thus, they contribute concurrently to the assessment of the pandemic’s impact and to the task of mitigating its effects.

**Renewables:** Ref. [2] provides valuable insights of grid stability issues in Great Britain due to the high penetration of non-synchronous renewables. Moreover, Ref. [2] assesses ancillary services used to guarantee stability, which proved to showcase significant cost increases. Additionally, a frequency-secured scheduling model is applied to verify future tendencies in Great Britain, as the country intends to reach net-zero emissions by 2050. Results demonstrate that ancillary services will be critical in the future due to the increasing penetration of renewable sources. Renewables are also the focus of Ref. [22], where renewable electricity transition planning is evaluated in New York based on a data-driven approach. The model proposed in [22] is highly robust and valuable to plan future environmentally-friendly electricity matrices. Furthermore, Ref. [22] demonstrates the usefulness of stochastic approaches compared to deterministic approaches. Stochastic/ensemble modeling is also presented in [23-27]. Ref. [2] also addresses renewables issues by developing a game theory model for optimizing multi-energy system design and renewable subsidy strategies. A two-phase decarbonization pathway is recommended in Ref. [28], i.e., first focusing on increasing the integration of renewables and then imposing emissions limits. Such a framework proved to be highly effective and might be valuable in the context of the sustainable energy transition. Lastly, the implications of the pandemic concerning the politics of renewable energy transitions are assessed in detail in...
### Table 1
Summary of additional literature review.

| Ref. | Country/region | Date of publication | Topics of interest | Work emphasis |
|------|----------------|---------------------|-------------------|--------------|
| [39] | USA            | Nov / 2021          | Electricity market | Wholesale electricity prices, evaluating aspects that can lead to negative prices, quantification of pandemic period and non-pandemic period variability in the electricity market. |
| [40] | Multiple regions | Feb / 2021          | Sensing and autonomous grids | Review of pervasive sensing techniques in power systems and development of autonomous energy grids (AEGs). |
| [41] | China          | May / 2021          | Circular economy   | Evaluation of energy demand and environmental gains for a circular economy scenario. |
| [42] | New York - USA | Jan / 2021          | Energy/ environment | Optimization of food-energy-water nexus systems in the context of the COVID-19 pandemic. |
| [43] | Multiple regions | Dec / 2020          | Emissions/air quality | Development of a policy alignment for a sustainable energy system post-COVID-19. |
| [44] | Multiple regions | Mar / 2021          | Emissions/air quality | Analysis of the future trends of power sector emissions. |
| [45] | Multiple regions | Jul / 2021          | Renewables         | Analysis of how the pandemic will influence sustainable energy development. |
| [46] | Jordan         | Jan / 2021          | Electricity demand | Analysis of the impact of the pandemic on electricity demand by eliminating correlation, trends, and seasonality. |
| [47] | Turkey         | Feb / 2021          | Electricity demand | Accurate forecast of electricity demand during the lockdown period. |
| [48] | Malaysia       | Nov / 2020          | Renewables         | Review of the status of renewables in Malaysia in the context of the pandemic. |
| [49] | Multiple regions | Oct / 2020          | Electricity demand, emissions/air quality, social aspects | Analysis of the impact of the pandemic on a range of topics (demand, climate change, social practices, etc.). |
| [50] | Europe         | Feb / 2021          | Emissions/air quality | Comparison of air pollution between non-pandemic period and pandemic period. |
| [51] | Multiple regions | Jun / 2020          | Emissions/air quality | Quantification of CO₂ variations in power generation, industry, road transportation, etc. |
| [52] | South Asia     | Dec / 2020          | Emissions/air quality | Analysis of the impact of the pandemic on air quality by determining the correlation between air quality, traffic volume, and meteorological conditions. |

### Table 1 (continued)

| Ref. | Country/region | Date of publication | Topics of interest | Work emphasis |
|------|----------------|---------------------|-------------------|--------------|
| [53] | São Paulo - Brazil | Aug / 2020          | Emissions/air quality | Comparison of air pollution between non-pandemic period and pandemic period. |
| [54] | Multiple regions | Feb / 2021          | Emissions/air quality | Quantification of CO₂ variations in power generation. |
| [55] | Multiple regions | Sep / 2020          | Environmental effects in general | Analysis of the impact of the pandemic on emissions, water pollution, noise pollution, biomedical waste, etc. |
| [56] | Multiple regions | Feb / 2021          | Emissions/air quality | Analysis of the impact of the pandemic on air quality by evaluating aspects that can lead to negative prices. |
| [57] | Multiple regions | Dec / 2020          | Emissions/air quality | Analysis of the future trends of power sector emissions. |
| [58] | China          | Feb / 2021          | Emissions/air quality | Analysis of the impact of the pandemic on air quality by determining the correlation between air quality, traffic volume, and meteorological conditions. |
| [59] | Nanjing - China | Nov / 2020          | Emissions/air quality | Analysis of the impact of the pandemic on air quality based on multiple low-cost sensors. |
| [60] | Florida - USA  | May / 2021          | Emissions/air quality | Comparison of air pollution between non-pandemic period and pandemic period. |
| [61] | Mexico City - Mexico | Mar / 2021 | Emissions/air quality | Comparison of air pollution between non-pandemic period and pandemic period. |
| [62] | Multiple regions | Jul / 2020          | Emissions/air quality | Analysis of the impact of the pandemic on air quality based on multiple low-cost sensors. |
| [63] | Europe         | Jan / 2021          | Renewables         | Analysis of the development of renewable energy sources and grid flexibility in the context of the pandemic. |
| [64] | USA            | Nov / 2020          | Electricity demand | Integration of pervasive sensing techniques in power systems and development of autonomous energy grids (AEGs). |
| [65] |                | Jul / 2020          |                   | (continued on next page) |
Ref. [29]. Ref. [29] affirms that the pandemic has exposed a lack of political responses to crises. Furthermore, geographical diversities are not taken into account seriously enough in the context of renewable energy transitions. Additionally, valuable insights regarding opportunities for improvement are provided from the pandemic experience. It can be verified that although [2,22,28,29] focus on renewables, the work emphasis is substantially different.
Table 2
VaR (Sum of all months for the concession area of CPFL Paulista)

| VaR(50%) | 6.80% |
| VaR(60%) | 3.38% |
| VaR(70%) | 5.91% |
| VaR(80%) | 5.36% |
| VaR(90%) | 4.57% |
| VaR(99.9%) | 3.94% |
| VaR(99.99%) | 1.44% |

Table 3
VaR (Sum of all months for the concession area of Cosern)

| VaR(50%) | 4.50% |
| VaR(60%) | 3.87% |
| VaR(70%) | 3.22% |
| VaR(80%) | 2.45% |
| VaR(90%) | 1.44% |
| VaR(95%) | 0.47% |
| VaR(99.9%) | -3.00% |

Emissions/air quality: Ref. [30] assesses heating, ventilation, and air-conditioning (HVAC) systems in the context of the pandemic, including airborne transmission characteristics of the virus (SARS-CoV-2), new guidelines to mitigate the transmission, and operational variations/innovations. Energy consumption variations are also assessed, and results demonstrate that HVAC energy consumption increased by 128% in China. Ref. [31] presents a work emphasis similar to Ref. [30], i.e., in-depth assessment of HVAC systems in the context of the pandemic. Ref. [31] demonstrates the energy cost of increasing outdoor air supply to limit infections and proposes a novel system that simultaneously decreases the risk of infections and energy cost. Results demonstrate that the proposed system is highly effective as energy costs decrease by 10–45% depending on the city (major cities worldwide were assessed). Ref. [32] analyzes the relationship between air pollution and COVID-19 impacts. The literature review demonstrated a high effort by the scientific community to mitigate the impact of the COVID-19 pandemic or to assess/plan the post-COVID-19 era, as the number of published papers has been increasing continuously. There seem to be a focus on the topics described above. The work emphasis differs considerably between

| Table 4
Summary of the pandemic’s impact.

|                      | Minimum impact (MR $/month) | Maximum impact (MR $/month) | Mean impact (MR $/month) | Standard deviation of the impact (MR $/month) |
|----------------------|-----------------------------|-----------------------------|--------------------------|---------------------------------------------|
| Cosern               | ECA (consumers’ surplus)    | 12.0                        | 175.6                    | 68.8                                        | 40.5                                        |
|                      | EVA (company’s surplus)     | -26.4                       | -1.0                     | -15.8                                       | 7.0                                         |
| Enel RJ              | ECA (consumers’ surplus)    | -260.2                      | 255.3                    | -38.7                                       | 121.9                                      |
|                      | EVA (company’s surplus)     | -90.6                       | -12.5                    | -49.3                                       | 23.4                                       |
| Energisa MT          | ECA (consumers’ surplus)    | -95.9                       | 240.2                    | 70.6                                        | 75.1                                       |
|                      | EVA (company’s surplus)     | -30.0                       | 2.8                      | -18.5                                       | 8.3                                        |
| Coelba               | ECA (consumers’ surplus)    | 360.5                       | 932.0                    | 478.1                                       | 165.2                                      |
|                      | EVA (company’s surplus)     | -138.7                      | 2.9                      | -67.5                                       | 41.1                                       |
| Energisa SE          | ECA (consumers’ surplus)    | -5.4                        | 70.9                     | 26.2                                        | 17.5                                       |
|                      | EVA (company’s surplus)     | -13.2                       | -0.4                     | -8.7                                        | 3.7                                        |
| CPFL Paulista        | ECA (consumers’ surplus)    | -91.8                       | 557.8                    | 189.6                                       | 158.8                                      |
|                      | EVA (company’s surplus)     | -122.2                      | -1.9                     | -66.8                                       | 33.1                                       |
| Equivalent concession area | ECA (consumers’ surplus)    | 213.7                       | 1905.1                   | 794.6                                       | 444.7                                      |
|                      | EVA (company’s surplus)     | -414.6                      | -13.1                    | -226.6                                      | 112.4                                      |

Table 5
VaR (Sum of all months for the equivalent concession area)

| VaR(50%) | 5.56% |
| VaR(60%) | 5.29% |
| VaR(70%) | 5.00% |
| VaR(80%) | 4.70% |
| VaR(90%) | 4.23% |
| VaR(95%) | 3.83% |
| VaR(99.9%) | 2.09% |
| VaR(99.99%) | 1.16% |
papers, i.e., pandemic-related issues are being analyzed based on several methodologies/points of view, contributing concurrently to speed up the recovery process and enhancing opportunities in the post-pandemic era. However, it is undeniable that most papers perform a past/present analysis of the impact of the pandemic; hence, a limited effort is being carried out to analyze the future impact of the pandemic. In the context of the COVID-19 pandemic, publications that focus on future simulations of the electricity market from a socioeconomic point of view have not been found, demonstrating the relevance of the methodology proposed in this paper.

Additional papers that tackle pandemic related issues are summarized in Table 1. Again, attention is drawn to the volume of publications; however, Table 1 demonstrates a research gap on socioeconomic analyses of the electricity market in the context of the pandemic. To evidence this, a bibliographic search was carried out in three databases: Scopus, Web of Science and IEEE Xplore. The advanced search was performed with the following keywords: COVID-19, electricity market, and socioeconomic. Similar terms were also taken into account (e.g., socio-economic) for more solid research. They should be present in the title, abstract, or keywords of the work. In IEEE Xplore, no articles were found as a result of the search. In Web of Science, only Ref. [9] was found (background of this paper). On the basis of Scopus, in addition to the previous reference [9], three more works were found. In [36], despite mentioning that the pandemic had socioeconomic impacts, the focus of the article is to propose a model for forecasting electricity price and demand based on the LSTM Deep Learning method considering recent demand trends in the Australian electricity market. In [37] the authors highlight the variation in energy demand as a direct and measurable impact of the pandemic on the electric sector and present a methodology to assess the effects of blockages on the European electric system. The study [38] presents a comparison of the marginal cost variation and how the economic crisis affected the Brazilian electricity market, in addition to bringing a discussion about the socio-economic implications for the electric sector in the post-pandemic period. The authors emphasize that the pattern of behavior in the consumption of electricity must be changed and conclude that the Brazilian electric sector must reformulate the existing regulatory policy in order to maintain the structure of the sector in the face of new crises. While Ref. [38] provides valuable perspectives, the assessment is mainly conducted based on load curves and marginal costs, and socioeconomic models/forecasting techniques are not applied. The post-pandemic assessment of Ref. [38] is based on philosophical discussions. Thus, the gap in studies that address economic issues, as well as impacts on society as a whole, and the novelty of the proposed model are highlighted again.

To cover the aspects related to energy systems in times of pandemic, even more in-depth research was carried out, especially concerning the notorious impacts of the COVID-19 pandemic on the surrounding socio-economic-energy triad around the world. Since different changes occur in different contexts for each country, we summarize this information together with the information in Table 1, generating the map in Fig. 1.

In the countries highlighted in Fig. 1, it was identified that, for the most part, the impacts resulting from the pandemic on the electric sector are directly related to the socio-economic aspects of each country/region. This fact was expected, as there is no way to isolate such phenomena in a global pandemic, where countless people were directly and indirectly impacted by COVID-19. In addition to the reduction in demand and variations in electricity consumption patterns, changes in the electric sector must deal with ethnic aspects, not just income (or both together), since the transition to remote work is only sustainable for groups above the middle class. Tariff designs need to be reformulated so that the low-income population is not further disadvantaged, especially in a post-COVID-19 context. Opening the space for dialogue on ethical issues in the context of the electric sector in a pandemic moment is essential, as energy infrastructures must consider the variety of lifestyles of populations that may or may not maintain themselves in remote work.

1.2.2. Publications concerning the optimized tariff model
Due to its effectiveness in modeling the regulated distribution electricity market, the TAROT model has been applied in several contexts. Among publications, stand out: socioeconomic feasibility assessment of ESS from society’s point of view, focusing on energy loss aspects [85]; evaluation of energy theft [86], which is a common issue in emerging countries; assessment of the effectiveness of public policies [87]; analysis of the influence of power quality in the market [88]; evaluation of increasing installed capacity of distributed generation (DG) [89] and aggregated analysis of regulated Brazilian power distribution companies [90]. Hence, the model is very flexible.
The application of the TAROT model in all studies mentioned above was conducted since it satisfactorily represents the Brazilian regulated electricity market and the tariff review procedures performed by the regulatory agency (National Electricity Agency - ANEEL). The TAROT model simplifies the tariff review procedures carried out by ANEEL (which is significantly intricate) while enabling accurate market assessment. In this context, whenever the Brazilian regulated electricity market is the object of study, the application of the TAROT model is satisfactory (the possibility of applying the TAROT model to other countries is discussed in Section 1.3). In conclusion, the TAROT model is suitable for this paper’s context. Furthermore, other advantages of the TAROT model should be mentioned: (i) it enables the assessment of the pandemic’s impact on consumers and distribution companies separately (this is important since results demonstrate that consumers were/will be significantly affected, unlike the companies), and (ii) it is a socioeconomic model (not only economic) since it quantifies the quality of life added by electricity consumption.

1.3. Novelty and contributions

This paper proposes major approach modifications/improvements in relation to the methodology applied in [9]. Ref [9] seeks to assess the impact of the COVID-19 pandemic on the Brazilian distribution electricity market by applying the TAROT. While [9] provides a valuable overview of the impact of the pandemic, the model is applied in a static context, i.e., the impact of the pandemic is not analyzed dynamically (time-series context). Moreover, a deterministic analysis is performed in [9], which is not satisfactory when performing a time-series assessment, as the electricity market presents inherent risks. Hence, the approach is modified from a static/deterministic analysis to a dynamic/stochastic analysis based on rigorous data processing. By doing so, this paper enables the accurate forecasting of the pandemic’s impact on the market. Furthermore, the pandemic’s impact is analyzed monthly in this paper, which is superior to the annual analysis conducted in Ref. [9] since it promotes the verification of critical periods. Moreover, Ref. [9] did not enable the analysis of the COVID-account’s future implications (public policy implemented by the Brazilian government), which is a considerable drawback since the interest rate introduced by such policy has major implications on consumers. As outlined, the approach modifications/improvements are very significant; thus, this paper proposes a novel/valuable methodology to assess the impact of the pandemic on the electricity market.

Although the TAROT has been applied for regulated electricity market modeling several times [9,85-90], this paper is the first of its kind in combining rigorous data processing/robust stochastic optimization with the TAROT. This is particularly important since the TAROT is widely applied in the Brazilian context; however, the model is usually applied independently, without forecasting/optimization or other techniques. The independent application of the TAROT limits its potential since many advanced applications rely on the usage of other techniques with the TAROT. Examples of potential advanced applications that can be assessed in future work based on the techniques mentioned above include forecasting the impact of electric vehicles (EVs) on the electricity market, and minimizing the economic loss of distribution companies with electricity theft in a stochastic context. Therefore, this paper is expected to open up new perspectives concerning the TAROT and enable future TAROT studies in several contexts, contributing to more in-depth analyses of the regulated electricity market.

The literature review demonstrated that, based on the current state-of-the-art, it is impractical to answer two critical questions (i) “from a socioeconomic point of view, how consumers and power distribution companies were/will be affected by the pandemic over time, taking into account the market’s risks?”; and (ii) “How to implement a robust public policy to mitigate the impact of the pandemic over time while satisfying the interests of the market agents (power distribution company and consumers) and government simultaneously?”. The proposed model regards a more complete approach than electricity demand studies (relatively common in the literature as detailed in Section 1.2.1) since it considers the quality of life added by electricity consumption. Moreover, previously proposed models/approaches typically enable past or future analyses of the pandemic. In contrast, the model developed in this paper is highly flexible, as it enables both past and future analyses and the formulation of robust stochastic public policies to mitigate the impact of the pandemic.

A great advantage of the TAROT model, as will be presented in Section 2.3, is the representation of the consumer through the utility function, proposed by Von Neumann and Morgenstern [91], which seeks to quantify the monetary equivalent of satisfaction in electricity consumption. This function is defined by the parameters of avidity and satiety (detailed in Ref. [9]), which can be calculated according to the demand elasticity data, electricity consumption, and tariff values for each region or country under analysis. Therefore, from the consumer’s point of view, the model is global.

It is important to emphasize that the TAROT was originally developed by Brazilian researchers to assess regulated distribution electricity markets, based on Stern Stewart’s value-added economic principle [92]. Thus, from the distribution companies’ point of view, the proposed model can be applied to:

- Regulated distribution electricity markets of countries/regions with a tariff structure equal to Brazil’s. In this case, adjustments are not necessary;
- Regulated distribution electricity markets of countries/regions with a tariff structure different from Brazil’s. However, in this case, adjustments are required in the TAROT, such as the expenses that are included in the tariff and operating costs involved. According to [93], the tariff structure of countries can vary, for instance, depending on government policies (e.g., climate policies) and taxes framework. Therefore, to apply the model to other countries/
regions, it is important to understand their tariff structure for potential adaptations. Ref. [85] is an example of TAROT model adaptation, where time-of-use rates are assessed instead of constant tariffs.

It should be noted, however, that the regulated aspect is essential to properly apply the TAROT. More specifically, the tariff is assumed to be controlled by the regulatory agency through tariff review processes, which present clear guidelines. Therefore, the TAROT is not recommended for highly competitive markets in the retail segment (e.g., Texas [94]) or for markets where the tariff formation does not present clear guidelines (e.g., bilateral contracts [95]). That being said, Brazil also presents highly competitive markets in the retail segment; however, only regulated markets are assessed in the model (which currently accounts for the majority of the country). Concerning the USA, electricity markets differ depending on the state; thus, the proposed model’s application is restricted to states with the characteristics mentioned above. Regarding China, according to [96], China’s electricity markets are currently undergoing a deregulation process (just as Brazil); however, full market liberation remains a long way off; thus, the proposed model can be a valuable tool. The USA and China are mentioned as examples due to their high electricity consumption; however, the same logic is valid for other countries/regions.

Brazil is the object of study in this paper due to two main reasons: (i) the ease of obtaining historical data required to apply the proposed model, and (ii) the importance of assessing the effectiveness of the COVID-account implemented by the government.

For clarity, Fig. 2 objectively describes the application of the proposed model and its contributions. As verified, historical data is separated into two groups, and the model is applied in parallel (data processing methods are further detailed in Section 2.4). Then, the analysis is carried out by comparing the results.

It is important to emphasize that although the proposed model is applied in the context of the COVID-19 pandemic in this paper, it can also be applied in the context of other crises, such as assessing the impact of an economic crisis on the electricity market. In order to do so, input data must be separated accordingly. In conclusion, the proposed model is flexible and a valuable tool for electricity market analysis.

2. Methodology

2.1. Assumed risks

In order to perform a detailed/accurate analysis, the following risks are addressed in this paper:

- Sales taxes;
- Tax fee;
- Grid depreciation;
- Capital yield;
- Tariff;
- Operational expenses;
- Consumed energy;
- Energy loss.

The risks mentioned above are introduced into the proposed model based on the software Oracle Crystal Ball®, which performs Monte Carlo simulations; however, other related software might also be applied.

2.2. Random walk

Random walk is the primary technique used for risk assessment in this paper. Based on this technique, the mean values, standard deviations, and growth tendencies of the stochastic variables are obtained, then these values are inserted into the software Oracle Crystal Ball®. The random walk theory assumes that the future is partly related to the past and partly related to unpredictability [97]. Mathematically:

\[
x_{k+1} = x_k \epsilon^\gamma + \epsilon_k
\]

where:

- \( \epsilon \) is Euler’s number (represented in bold to avoid future misunderstanding);
- \( x_{k+1} \) is the future value of the stochastic variable;
- \( x_k \) is the present value of the stochastic variable;
- \( \gamma \) is the growth (or reduction) tendency of the stochastic variable.
- \( \epsilon_k \) is a random noise with zero mean and finite standard deviation. In order to accurately calculate the standard deviation and generate accurate random numbers, historical series of the input data are required.

In Brazil, ANEEL provides data from 2014 onwards [98], used in this paper to apply the random walk concept. Fig. 3 illustrates an example in which the random walk concept can be applied (data from [99]). It can be easily verified that the Brazilian electricity consumption presents a growth tendency in the long-term (\( \gamma \)), however, significant variability is observed (\( \epsilon_k \)). Hence, it is essential to generate random noises to model such behavior accordingly. While
Fig. 3 exemplifies one iteration, in practice, thousands of iterations are performed by the software so that results are accurate. Estimating random variables becomes more complex over time. Therefore, the standard deviations must be continuously recalculated to model risk escalation [97].

2.3. Optimized tariff model

As previously mentioned, this paper applies the TAROT model since it appropriately represents the Brazilian regulated electricity market and the tariff review procedures performed by ANEEL, enabling accurate market assessment.

The primary benefit of the TAROT model is that it models the whole electricity market, and not just the power distribution company, as it aggregates both production and consumption. Moreover, consumers are represented simply and objectively. Furthermore, it is highlighted that the model is based on added value/welfare and not just a balance of results, thus allowing the evaluation of all agents involved in the electricity market separately.

As [9] has already presented the former TAROT model in detail (including the obtention of the parameters), this section summarizes the most critical aspects and equations. Fig. 4 presents the model’s diagram, with the main variables involved, which will be presented below. It is important to emphasize that, as pointed out in Section 2.1, the parameters/variables are treated as stochastic and time-dependent; however, these notations are omitted to simplify the equations.

The left rectangle in Fig. 4 represents the surpluses of the market players, i.e., the players’ benefit from the economic transaction (sale/purchase of electricity). Economic Consumer Added (ECA) regards the consumers’ benefit, which is modeled based on the quality of life added by electricity consumption (utility) subtracted from the amount paid for consumption (revenue or electricity bill paid to the distribution company). Consumers are modeled this way since the utility/quality of life is what they seek, whereas the revenue/electricity bill is seen as a detriment from their point of view. In contrast, the distribution companies seek revenue; hence, the distribution company’s surplus (Economic Value Added - EVA) is modeled based on the revenue subtracted from all the costs involved in the company’s operation (logically, the costs are seen as a detriment for companies). As verified in Fig. 4, several types of costs are involved in the regulated electricity market (sales taxes, operational costs, depreciation, taxes over profits, and capital yield), which are quantified in the TAROT model. Finally, Economic Wealth Added (EWA) represents society’s benefit from the economic transaction, which is given by the consumers’ benefit (ECA) summed with the company’s benefit (EVA).

2.3.1. Consumers’ model

The utility function is composed of the parameters of avidity and satiety for electricity consumption, which represent the consumer’s desire to consume energy and the degree of satisfaction with energy.
consumption, respectively, according to the expression:

$$ U = aE - \frac{b}{2}E^2 $$  \hspace{1cm} (2)

where:

- $a$ is the avidity parameter (desire to consume energy or willingness to pay);
- $b$ is the satiety parameter (degree of satisfaction with the consumed energy);
- $E$ is the consumed energy.

The TAROT is classified as a socioeconomic model rather than purely economic due to this representation. The consumers’ surplus in (MR$) is given by:

$$ ECA = U - TE $$  \hspace{1cm} (3)

where:

- $TE$ models the revenue (or electricity bill) paid to the power distribution company;
- $T$ is the tariff.

2.3.2. Regulated power distribution company’s model

The power distribution company’s surplus in (MR$) is given by:

$$ EVA = (1 - t) \left\{ R - \left[ \frac{E}{B} + \mu + \frac{p}{B}E^2 + \mu R + B(\frac{r_w}{1 - t}) \right] \right\} $$  \hspace{1cm} (4)

where:

- $t$ is the tax fee;
- $\mu$ is the sales taxes parameter;
- $e$ is the operational expenses parameter;
- $p$ is the energy loss parameter;
- $B$ is the grid investment;
- $d$ is the grid depreciation parameter;
- $r_w$ is the capital yield parameter;
- $E$ is the consumed energy;
- $R$ is the revenue defined in (3).

The optimal grid investment ($B^*$) is expressed by:

$$ \frac{\partial EVA}{\partial B} = 0 \Rightarrow B^* = \sqrt{\frac{\mu}{e}} \cdot E $$  \hspace{1cm} (5)

where $k = d + r_w/(1 - t)$ is the “hurdle rate” for aggregation of value to the regulated company.

Hence, from (4) and (5), i.e., assuming that the power distribution company is a rational agent with the predefined goal of maximizing its surplus (EVA):

$$ EVA = (1 - t) \left[ (a - \mu a - E - 2\sqrt{pk} )E + (\mu b - b)E^2 \right] $$  \hspace{1cm} (6)

2.3.3. Overall socioeconomic model

The socioeconomic welfare, i.e., the overall benefit of society arising from the transaction of electricity, is given by:

$$ EWA = ECA + EVA $$  \hspace{1cm} (7)

The regulatory agency seeks to maximize the socioeconomic welfare of the market. As pointed out in [9], the power distribution companies are usually in a state of financial-economic equilibrium (FEE), i.e., the regulatory agency maintains EVA close to zero to ensure fair tariffs. Thus, considering that the regulatory agency seeks to adjust tariffs so that the EVA is as close to zero as possible, and analyzing (7), it is concluded that the added economic value for society as a whole, due to the distribution service of electricity, will be approximately equal to the consumer’s surplus, i.e., $EVA \cong ECA$. In the case study performed in Section 3, this is assumed so that the results/figures are not practically replicated by presenting both ECA and EWA.

2.4. Data processing and proposed algorithm

In this section, data processing and the applied algorithm are presented in detail. The database used for the simulations is provided by ANEEL through reports of tariff distribution processes [98]. An essential concept is that the TAROT model has only been previously applied on an annual basis. However, for this paper’s proposal, such a time basis would not be suitable for two main reasons: (i) it limits the historical database required for risk assessment; (ii) it regards a medium-term analysis exclusively. Therefore, the time basis is modified from annual to monthly, enabling accurate short-/medium-term analyses. In this context, some parameters are fixed by ANEEL for the whole year (e.g., tariff). For such parameters, a random number is generated by the software in the month when there is a tariff review (this occurs once a year for each concession area). Then, the generated random number is maintained for the rest of the year. For the parameters that the regulatory agency does not fix, i.e., consumption and energy loss parameters, random numbers are generated monthly. This approach ensures that the analysis is following the procedures carried out by ANEEL. However, it is essential to emphasize that the regulatory agency’s procedures might vary depending on the country/region; thus, being familiar with the procedures is essential to apply the proposed model properly.

In Brazil, there are pronounced seasonalties related to electricity consumption; thus, it is essential to consider such issues when performing a monthly analysis to improve the accuracy of the simulations (the seasonality proved to be even more influential than the growth tendencies in the short-/medium-term). It is assumed that the seasonality prior and following the pandemic is equal since data is limited to assume distinct seasonabilities. In this paper, the random walk with seasonality prior and following the pandemic period as it was roughly when the pandemic took place in Brazil [101]. From this step, all further steps are conducted in parallel, i.e., they are conducted for each of the two groups independently (except for the interpretation step).

**Step 4:** elimination of the seasonality. The seasonality is removed by dividing the historical data by the seasonality indexes;

**Step 5:** performing exponential regressions on data from Step 4 to obtain the growth tendencies. The exponential regressions present increased accuracy since the seasonality was removed;

**Step 6:** calculating the mean/expected values of the random variables over time based on Eq. (8):
where:

$\dot{e}$ is Euler’s number (represented in bold to avoid confusion with the parameter $e$ from the TAROT);

$i$ is the month;

$E_i$ is the electricity consumption in month $i$;

$E_{i-1}$ is the electricity consumption in month $i - 1$;

$\gamma_E$ is the growth tendency of the electricity consumption;

$\theta_{E_i}$ is the seasonality index of the electricity consumption in month $i$;

$\theta_{E_{i-1}}$ is the seasonality index of the electricity consumption in month $i - 1$.

While Eq. (8) exemplifies the calculation of the electricity consumption, the same procedure is carried out for the energy loss parameter ($p$), as equated in (9):

$p_i = \left( \frac{\theta_{E_i}}{\theta_{E_{i-1}}} \right) e^{\gamma_p} p_{i-1} \tag{9}$

where the parameters in Eq. (9) are analogous to those in Eq. (8).

The mean values are then inserted into the software Oracle Crystal Ball®.

Step 7: calculating the standard deviations. The standard deviations are calculated by comparing the model’s estimation (Eqs. (8) and (9)) and the historical data. The standard deviations are then inserted into the software Oracle Crystal Ball®;

Step 8: generation of multiple random numbers based on Steps 6, 7, and the software Oracle Crystal Ball®;

Step 9: Monte Carlo simulations, i.e., the TAROT model equations presented in Section 2.3 are applied for every iteration and every month, using the random numbers generated by the software;

Step 10: after multiple iterations, the software provides the mean values and standard deviations of the market agents’ surpluses (agents’ benefits due to the economic transaction) for every month, along with other statistics. Then, these values are plotted over time;

Step 11: interpreting the results by comparing the plots between the prior and post-pandemic simulations and by calculating key metrics such as the value at risk (VaR).

In reality, Steps 8, 9 are performed simultaneously by the software but have been separated here for a better understanding.

The proposed algorithm is also presented in Fig. 5 for ease of viewing:

It is important to emphasize that Jan / 2020 regards the most recent information in a non-pandemic context, whereas reference date Mar / 2021 regards the most recent information in a pandemic context [98]. Hence, Jan / 2020 is assumed to be the starting simulating point for the pre-pandemic scenario, whereas Mar / 2021 is assumed to be the starting simulating point for the post-pandemic scenario.
For better contextualization, Fig. 6 illustrates the model’s estimation (Eq. (8)) compared to historical data for the concession area of Enel RJ (concession area further evaluated in the case study). Although the proposed model presents satisfactory accuracy, the standard deviation is significant, i.e., risk assessment is of utmost importance. The model’s mean absolute percentage error (MAPE) is presented in the Appendix section (Table A1).

### 3. Case study

#### 3.1. Initial considerations

In order to properly assess the impact of the pandemic and guarantee solid results, the proposed model is applied to six Brazilian concession areas (Cosern, Enel RJ, Energisa MT, Coelba, Energisa SE, and CPFL Paulista). For better contextualization, Table A2 in the Appendix section presents additional information from the concession areas. Such concession areas were selected since ANEEL has already provided their data from 2021. Hence, the monthly parameters can be separated into two groups (prior and post-pandemic), as described in Table A3 in the Appendix. Data from 2015 to 2020 were used to obtain information prior to the pandemic, whereas data from Jan / 2020 onwards were used to obtain information after the occurrence of the pandemic [98]. There is considerable variability of growth tendencies and standard deviations among concession areas, highlighting the importance of applying the model to multiple concession areas. It should be noted that a decrease in the energy loss parameter \( p \) during the pandemic does not necessarily mean that the pandemic has reduced energy loss, as the \( p \) parameter also depends on the energy price in the wholesale market [9].

Table A4 in the Appendix presents information regarding the parameters fixed annually by ANEEL. The tax fee parameter \( t \) is omitted since it does not present a growth tendency or standard deviation. There is not enough data for such parameters to separate them into prior and post-pandemic groups yet since the pandemic occurred roughly fifteen months ago. However, once more data is released by ANEEL (in the following years), it might be possible to assume two distinct groups for them and ensure increased accuracy. Data from 2014 onwards were used to obtain the information in Table A4 [98].

Table A5 in the Appendix presents the initial market conditions for the two different reference dates (Jan / 2020 - initial month for the non-pandemic simulation; Mar / 2021 - initial month for the pandemic simulation). The tax fee parameter \( t \) is omitted in Table A5 since it is always equal to 34% in Brazil for all concession areas, as they are federal states.

| Concession area | MAPE |
|-----------------|------|
| Cosern          | 2.13%|
| Enel RJ         | 2.85%|
| Energisa MT     | 3.41%|
| Coelba          | 2.23%|
| Energisa SE     | 2.36%|
| CPFL Paulista   | 3.14%|

Table A2

| Concession area | State            | Region | Number of consumer units |
|-----------------|------------------|--------|--------------------------|
| Cosern          | Rio Grande do Norte (RN) | Northeast | 1,479,295               |
| Enel RJ         | Rio de Janeiro (RJ)    | Southeast | 2,648,762               |
| Energisa MT     | Mato Grosso (MT)       | Midwest | 1,462,913               |
| Coelba          | Bahia (BA)            | Northeast | 6,123,498               |
| Energisa SE     | Sergipe (SE)          | Northeast | 789,783                |
| CPFL Paulista   | São Paulo (SP)        | Southeast | 4,515,316               |

| Non-fixed parameters by ANEEL | \( E \) (TWh) | Monthly growth tendency \( \gamma \) prior to the pandemic | Monthly growth tendency \( \gamma \) following the pandemic |
|-------------------------------|--------------|-------------------------------------------------|-------------------------------------------------|
| Cosern                         | 0.012        | 0.04%                                           | 0.08%                                           |
| Enel RJ                        | 0.035        | 0.2%                                            | -0.3%                                          |
| Energisa MT                   | 0.030        | 0.02%                                           | 0.05%                                          |
| Coelba                        | 0.049        | 0.5%                                            | -0.08%                                         |
| Energisa SE                   | 0.051        | 0.1%                                            | 0.2%                                           |
| CPFL Paulista                 | 0.038        | 0.2%                                            | 0.2%                                           |

Table A3

**Table A4** Initial standard deviations.
Finally, Table A6 in the Appendix presents the obtained seasonality indexes. Based on Tables A.3-A.6, results can be replicated.

3.2. Results and analysis

For highly accurate results, a total of 10,000 Monte Carlo iterations are performed. For better visualization, simulation results are separated into the past impact of the pandemic (from Jan / 2020 to Mar / 2021) and the future impact of the pandemic (Apr / 2021 onwards). The results of both Cosern and CPFL Paulista are thoroughly discussed/assessed in Sections 3.2.1, 3.2.2, while the results of Enel RJ, Energisa MT, Coelba, and Energisa SE are summarized in Section 3.2.3. Section 3.2.4 conducts philosophical discussions of what would be the impact of the pandemic on the electricity market in a context where the regulatory agency does not intervene such noticeably. Moreover, critical conclusions are presented in Section 3.2.5. Finally, Section 3.2.5 discusses the robustness of the results by varying parameters/considerations that may be seen as debatable.

3.2.1. Cosern

Figs. 7, 8 exhibit the past estimated/simulated pandemic’s impact on the consumers’ surplus (ECA) and the power distribution company’s surplus (EVA) for the concession area of Cosern. Both ECA and EVA that took place with the pandemic were calculated based on data from the regulatory agency [98]; thus, there are no associated standard deviations since they are quantities that have already occurred in practice. On the other hand, it is impossible to know for sure how the market would operate if the pandemic had not taken place; hence, there are standard deviations (risks) associated with the non-pandemic simulation. Fig. 7 demonstrates that the pandemic decreased the expectation of EVA. Such a result is directly related to the increased the expectation of EVA. Both ECA and EVA that took place with the pandemic were calculated based on data from the regulatory agency [98]; thus, there are no associated standard deviations since they are quantities that have already occurred in practice. On the other hand, it is impossible to know for sure how the market would operate if the pandemic had not taken place; hence, there are standard deviations (risks) associated with the non-pandemic simulation. Fig. 7 demonstrates that the pandemic decreased the expectation of EVA. Such a result is directly related to the increased the expectation of EVA.

Table A4
Annual parameters.

|                      | Standard deviation (%) | Annual growth rate (%) |
|----------------------|------------------------|------------------------|
| sales taxes (μ)      |                        |                        |
| grid depreciation (d)|                        |                        |
| Capital yield (rC)   |                        |                        |
| Operational costs (c)|                        |                        |
| Tariff (T)           |                        |                        |

|                      | Initial standard deviations. |
|----------------------|-----------------------------|

Table A5
Initial market conditions.

|                      | E (TWh/month) | p (MR$/TWh) | μ (%) | d (%) | rC (%) | e (MR$/TWh) | T (MRS/TWh) |
|----------------------|---------------|-------------|-------|-------|--------|-------------|--------------|
| Reference date       | Jan / 2020   | Mar / 2020  | Jan / 2021 | Mar / 2021 | Jan / 2020 | Mar / 2021 | Jan / 2020 | Mar / 2021 | Jan / 2020 | Mar / 2021 | Jan / 2020 | Mar / 2021 | Jan / 2020 | Mar / 2021 | Jan / 2020 | Mar / 2021 | Jan / 2020 | Mar / 2021 |
| Cosern               | 5.50E-01     | 4.85E-01    | 1.10E+01 | 1.60E+01 | 2.57E+01 | 2.55E+01 | 3.98E-01 | 3.98E-01 | 8.09E-01 | 8.09E-01 | 3.19E+01 | 3.89E+01 | 5.75E+01 | 7.46E+01 |
| Enel RJ              | 1.06E+01     | 9.88E-01    | 2.56E+01 | 3.92E+01 | 2.96E+01 | 2.67E+01 | 4.26E-01 | 4.26E-01 | 8.09E-01 | 8.09E-01 | 3.94E+01 | 4.81E+01 | 7.22E+01 | 8.95E+01 |
| Energisa MT          | 7.32E-01     | 7.88E-01    | 2.07E+01 | 2.73E+01 | 2.83E+01 | 2.73E+01 | 3.70E-01 | 3.70E-01 | 8.09E-01 | 8.09E-01 | 4.01E+01 | 4.92E+01 | 7.55E+01 | 1.01E+02 |
| Coelba               | 1.77E+01     | 1.77E+01    | 1.63E+01 | 2.20E+01 | 2.74E+01 | 2.74E+01 | 3.94E-01 | 3.94E-01 | 8.09E-01 | 8.09E-01 | 3.12E+01 | 3.89E+01 | 6.24E+01 | 8.06E+01 |
| Energisa SE          | 2.64E-01     | 2.69E-01    | 9.64E+01 | 1.20E+01 | 6.60E+01 | 6.57E+01 | 3.81E-01 | 3.81E-01 | 8.09E-01 | 8.09E-01 | 3.06E+01 | 3.67E+01 | 5.29E+01 | 6.71E+01 |
| CPFL Paulista        | 2.12E+01     | 2.05E+01    | 1.12E+01 | 1.33E+01 | 2.48E+01 | 2.32E+01 | 3.72E-01 | 3.72E-01 | 8.09E-01 | 8.09E-01 | 3.73E+01 | 4.54E+01 | 6.53E+01 | 7.93E+01 |

Table A6
Seasonality indexes.

|                      | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|----------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Cosern               |     |     |     |     |     |     |     |     |     |     |     |     |
| Energy loss parameter (μ) | 1.04E+01 | 9.90E+00 | 8.90E+00 | 1.04E+01 | 9.80E+00 | 8.80E+00 | 9.80E+00 | 1.04E+01 | 9.90E+00 | 8.90E+00 | 1.04E+01 | 9.90E+00 |
| Enel RJ              |     |     |     |     |     |     |     |     |     |     |     |     |
| Energy loss parameter (μ) | 1.09E+01 | 1.09E+00 | 1.10E+00 | 1.09E+01 | 1.09E+00 | 1.10E+00 | 1.09E+00 | 1.09E+01 | 1.10E+00 | 1.10E+00 | 1.09E+01 | 1.10E+00 |
| Energisa MT          |     |     |     |     |     |     |     |     |     |     |     |     |
| Energy loss parameter (μ) | 9.90E-01 | 9.90E-01 | 9.90E-01 | 9.90E-01 | 9.90E-01 | 9.90E-01 | 9.90E-01 | 9.90E-01 | 9.90E-01 | 9.90E-01 | 9.90E-01 | 9.90E-01 |
| Coelba               |     |     |     |     |     |     |     |     |     |     |     |     |
| Energy loss parameter (μ) | 1.03E+01 | 1.03E+00 | 1.03E+00 | 1.03E+01 | 1.03E+00 | 1.03E+00 | 1.03E+00 | 1.03E+01 | 1.03E+00 | 1.03E+00 | 1.03E+01 | 1.03E+00 |
| Energisa SE          |     |     |     |     |     |     |     |     |     |     |     |     |
| Energy loss parameter (μ) | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 |
| CPFL Paulista        |     |     |     |     |     |     |     |     |     |     |     |     |
| Energy loss parameter (μ) | 1.04E+01 | 1.04E+01 | 1.04E+01 | 1.04E+01 | 1.04E+01 | 1.04E+01 | 1.04E+01 | 1.04E+01 | 1.04E+01 | 1.04E+01 | 1.04E+01 | 1.04E+01 |
| Energy loss parameter (μ) | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 | 9.90E+00 |
pandemic (this fact is further highlighted in the future analysis of the impact of the pandemic as the pattern is repeated). Sudden variations of ECA and EVA in the non-pandemic simulation (standard deviations) are verified in month 4 since April is when the tariff review process of Cosern occurs. Therefore, there is increased risk past April due to the generation of multiple random variables by the software Oracle Crystal Ball®. Regarding the mean values, ECA decreases in month 4, while EVA increases due to the tendency of a tariff raise by the regulatory agency. It can also be verified that the mean EVA of the non-pandemic simulation and the EVA that took place with the pandemic are very similar for the first three months of simulation, i.e., before market intervention by the regulatory agency.

Figs. 9, 10 exhibit the future estimated/simulated pandemic’s impact on the consumers’ surplus (ECA) and the power distribution company’s surplus (EVA) for the concession area of Cosern. Fig. 9 demonstrates that the pandemic will probably drastically reduce the consumers’ surplus since the initial tariff of the pandemic simulation is approximately 30% higher than that of the non-pandemic simulation, severely harming the consumers. It is emphasized that the consumption growth tendencies of Cosern prior and following the pandemic are very similar. Therefore, if the regulatory agency had homologated a standard tariff following the pandemic, the simulations of Fig. 9 would be very similar. Fig. 10 demonstrates that, due to the high tariff validated by the regulatory agency, the pandemic will not likely harm the power
distribution company (Cosern) even though the energy loss parameter increased substantially following the pandemic. However, the decreasing behavior of the pandemic simulation in Fig. 10 is due to the substantial growth tendency of the energy loss parameter.

While the representation of the standard deviations is mathematically appropriate, it might overshadow a quick evaluation of the involved risks. Therefore, Fig. 11 illustrates the mean pandemic’s impact and the probability of the pandemic having harmed the market in the past/harming the market in the future (concession area of Cosern). The probability is quantified as the number of pandemic iterations that were worse than non-pandemic iterations divided by the total number of iterations. A negative mean pandemic’s impact implies that the pandemic increased the average of the surplus. As verified, the mean ECA impact is typically 50 (MR$) or higher, whereas the mean EVA impact is between –25 and 0 (MR$). The probability of the pandemic having harmed the power distribution company in the past/harming the power distribution company in the future is typically close to 20–30%; thus, the effect of the pandemic on the power distribution company’s surplus is mitigated. In contrast, there is typically more than a 75% probability of the pandemic having harmed consumers in the past/harming consumers in the future.

Fig. 9. Future estimated pandemic’s impact on the consumers’ surplus (ECA) for the concession area of Cosern.

Fig. 10. Future estimated pandemic’s impact on the power distribution company’s surplus (EVA) for the concession area of Cosern.
In conclusion, the high tariff homologated by the regulatory agency is expected to affect the market remarkably.

For superior insights, the VaR calculation is of utmost importance. The VaR is calculated for the consumers (based on ECA) since the case study demonstrates that the pandemic’s impact on distribution companies is meager. As in this case, the objective is to verify if the pandemic truly impacted the consumers, the VaR is calculated as the minimum impact in percentage terms for a given confidence level. This concept is somewhat different from usual VaR applications in finances, which quantify the minimum expected return of the investment. In finances, the assumed confidence levels are usually around 95–99%; however, we assume a broader range of confidence levels for more solid conclusions. For instance, VaR(50%) roughly indicates the mean pandemic impact and is a useful metric. Fig. 12 illustrates the VaR as a time-series for the concession area of Cosern assuming five confidence levels (50%, 60%, 70%, 80%, 90%). Taking VaR(90%) in month 2 as an example, results indicate that it is equal to 1.58%; thus, 90% of iterations present an impact higher than 1.58%. Depending on the month/confidence level, the VaR for the past simulation (from Jan/2020 to Mar/2021) varies between −1.94% and
16.50%. For the most impactful month (Dec/2020), VaR(90%) is equal to 12.96%, indicating a severe impact. For the future simulation (from Apr/2021 to Apr/2022), the VaR(80%) is very close to zero, which indicates that the pandemic is impactful in about 80% of iterations (this is corroborated by Fig. 11).

Table 2 represents the VaR no longer as a time-series, but rather calculated based on the sum of ECA for all months. As verified, the overall impact on consumers is higher than 1.44% in 99.9% of iterations, proving that the impact is statistically significant.

3.2.2. CPFL Paulista

Figs. 13, 14 exhibit the past estimated/simulated pandemic’s impact on the consumers’ surplus (ECA) and the power distribution company’s surplus (EVA) for the concession area of CPFL Paulista. Fig. 13 illustrates some shape similarities between the past non-pandemic simulation and the EVA that took place with the pandemic, indicating that the model is properly representing the electricity market (naturally, the shapes are not identical as there is an associated risk). As verified, similar qualitative results to those of Cosern were obtained, i.e., the pandemic was in general harmful to consumers and beneficial for the power distribution company. Month 10 is an exception for the consumers as the consumed energy was unlikely high (98% percentile in the historical series). Such a result is once again directly related to the high tariff validated by the regulatory agency in the context of the pandemic.
Figs. 15, 16 exhibit the future estimated/simulated pandemic’s impact on the consumers’ surplus (ECA) and the power distribution company’s surplus (EVA) for the concession area of CPFL Paulista. Once again, results demonstrate that the pandemic will likely harm consumers while the power distribution company will not likely be harmed. Results also demonstrate a significant risk associated with EVA since CPFL Paulista is a large-scale company, and a slight variation of the parameters results in a large variation of EVA.

The mean impact and the probability of the pandemic having harmed the market in the past/harming the market in the future is illustrated in Fig. 17 (concession area of CPFL Paulista). As verified, Month 10 is an exception due to the 98% percentile consumed energy. The probability of the pandemic having harmed consumers in the past/harming consumers in the future is typically higher than 50%; however, it is mitigated in the medium-term (the ECA curve decreases over time) due to the positive consumption growth tendency following the pandemic. Besides the positive consumption growth tendency, the tariff of CPFL Paulista increased by 21% from 2020 to 2021, whereas the tariff of Cosern increased by 30%; hence, by comparing Fig. 11 and Fig. 17, it can be concluded that the consumers of CPFL Paulista were/will be less affected.

The VAR is represented in Fig. 18 as a time-series (based on ECA).
Fig. 17. Mean impact and probability of the pandemic harming the market for the concession area of CPFL Paulista.

Fig. 18. Time-series VaR for the concession area of CPFL Paulista.
Once again, it can be verified that the pandemic’s impact is mitigated in the medium-term (specific case of CPFL Paulista), as the VaR curves present decreasing behavior.

Finally, Table 3 represents the VaR based on the sum of ECA for all months. As verified, the results indicate less statistical significance of the pandemic’s impact compared to Cosern; however, an impact higher than 0.47% in 95% of iterations is still remarkable.

3.2.3. Summary of the results

Table 4 summarizes the results for the six analyzed concession areas (from Jan / 2020 to Apr / 2022). Once again, a negative mean pandemic’s impact implies that the pandemic increased the average of the surplus. Enel RJ is the only concession area in which the pandemic simulation was beneficial to consumers on average since, in this case, the pandemic did not increase the tariff significantly in relation to the natural trend of the market. The pandemic simulation was beneficial for all power distribution companies on average. The results for an equivalent concession area are also presented in Table 4, i.e., the sum of the impact of the six analyzed concession areas. By applying (7), the high tariffs homologated by ANEEL in the context of the pandemic led to socioeconomic losses on the order of 500 (MR$/month) for the equivalent concession area.

Finally the VaR for the equivalent concession area is described in Table 5 (based on ECA). The pandemic’s impact on consumers is evident.
as it is higher than 1.16% in virtually all iterations. In percentage terms, the mean impact is of 5.55%.

3.2.4. Philosophical discussions

Overall, the database available in [98] indicated that the regulatory agency increased the tariffs remarkably after the pandemic took place. This is likely related to the public policy proposed by the Brazilian government to mitigate the impact of the pandemic (COVID-account), which inserted an interest rate in the tariffs of 5.2% + inflation rate p.a. [102], due to a total of 16,100 (MR$) granted in loans to power distribution companies. Therefore, consumers must pay the interest rate alongside the regular annual tariff growth tendency (typically 7–10% p. a. depending on the concession area). Results demonstrated that such an increase in tariffs tends to harm consumers considerably. In fact, the tariff impact on ECA tends to overcome the consumption growth tendency impact, particularly in the short-/medium-term. While it is essential to ensure a state of FEE for the power distribution company (EVA close to zero with reasonable risk), the increase in the tariffs must be acceptable, since the purpose of creating the COVID-account was to prevent all company’s costs associated with the pandemic from being passed on to consumers in the next readjustment. With the measure of the government, due to the loans given, the “cost of the pandemic” will be amortized over five years, with the mentioned interest rate. This means that we should expect high tariffs due to the pandemic for the next four years at least.

Regarding the impact of the pandemic on the electricity market in the context of regular tariffs (overlooking excessive external intervention), the results are entirely dependent on the growth tendencies and standard deviations of the consumption and energy loss parameter before and following the pandemic. The subsequent conclusions were obtained based on the study carried out in this paper:

- Contrary to common sense, data from Jan / 2020 to Mar / 2021 (assumed to be the pandemic period) do not indicate a tendency of consumption decrease for the concession areas analyzed in the case study compared to the non-pandemic period. This might be related to three factors: (i) Brazil went through a period of economic crisis a few years ago; hence, the consumption growth tendencies before the pandemic were likely affected by such crisis, (ii) the TAROT model typically takes into account only the regulated market, i.e., the deregulated market (also known as free market), which generally comprises large-scale industrial consumers that vary demand more intensely is not accounted for, and (iii) energy consumption of the TAROT model includes non-technical losses (energy theft), which is known to have increased in Brazil following the pandemic [103]. However, it is emphasized that only six concession areas (less than 10% of the total) were analyzed since the regulatory agency has not released data from 2021 for most concession areas. As demonstrated in [9], the impact of the pandemic varies extensively depending on the concession area; thus, a general conclusion of the impact of the pandemic on the Brazilian electricity market considering risk assessment and a time-series approach will only be possible after more data is released;
- Regarding the energy loss parameter, some companies managed to reduce its growth tendency even in the face of the pandemic (Enel RJ, Coelba, Energisa SE, and CPFL Paulista), which indicates that such companies are investing in the network more efficiently. It is emphasized, however, that the energy loss parameter also depends on the energy price in the wholesale market and on non-technical losses [9];
- Although the applied forecasting technique presented satisfactory accuracy, stochastic assessment proved to be essential, as the standard deviations should not be neglected and the VaR evaluation provide superior insights compared to a deterministic analysis;
- The public policy proposed by the government (COVID-account) proved to be a short-term solution. The main idea of the policy was to reduce the tariffs in 2020 by granting loans to power distribution companies. However, the proposed model demonstrated that in the medium-/long-term, the interest rates will likely harm consumers (the loan will be paid for the next five years [102]). In conclusion, the development of long-term/sustainable public policies is essential to ensure proper market operation in the face of critical occurrences such as the COVID-19 pandemic.

3.2.5. Discussion regarding considerations

This section is dedicated to varying parameters/considerations that may be seen as debatable and assessing the changes in results (similarly to a sensitivity analysis). For transparency, the data is made available as supplementary material [104].

As previously mentioned, this paper initially assumed that the pandemic period initiated in Jan / 2020 as it was roughly when the pandemic took place in Brazil [101]. However, it is fair to state that the real effects of the pandemic on the electricity market might have taken a little longer to arise. Therefore, the first consideration to be varied is the separation of the data into pre-pandemic/post-pandemic periods for the calculation of tendencies (data reprocessing). The tendencies are calculated based on Feb / 2020, i.e., after WHO declared the status of international public health emergency [105] and Brazil started implementing legal measures to fight the pandemic [106]. In this case, the overall impact of the pandemic on ECA is 724.4 (MR$), representing a 9% change in relation to the impact obtained in Section 3.2.3, whereas the overall impact on EVA is –228.0 (MR$), representing a 1% change. Therefore, the effects of trend modifications are not particularly high.

The second consideration to be changed is the initial market conditions, based on the same logic as the previous paragraph. By doing so, the overall impact of the pandemic on ECA and EVA are 598 (MR$) and –211.6 (MR$), respectively, representing a 25% change for the consumers and 7% for the companies. Therefore, the initial market conditions are significantly influential.

Regarding seasonality indexes, it was initially assumed that they were equal prior and following the pandemic. However, as demonstrated by Fezzi et al. [107], the containment policies might significantly influence seasonality. Therefore, the third consideration to be varied is to assume distinct seasonabilities. In this case, the overall impact of the pandemic on ECA and EVA are 900.9 (MR$) and –328.0 (MR$), respectively, representing a 13% change for the consumers and 44% for the companies. Therefore, seasonality is also significantly influential.

While both the initial market conditions and seasonality indicated a significant effect on results, it can be verified that the main conclusions of this paper are the same, i.e., the pandemic implied a substantial decrease in ECA and a substantial increase in EVA in all simulations, on the order of hundreds of (MR$). It is also relevant to emphasize that a relatively long period was assessed in this section (from Feb / 2020 to Apr / 2022), which contributes to more significant variations of ECA and EVA. That being said, it is important to assess these issues more closely in future work. For instance, once more data is released by ANEEL, it might be possible to separate the prior/post-pandemic periods with higher statistical rigor and assess if the pandemic indeed modified seasonality in the Brazilian regulated market. Furthermore, it might be beneficial to apply an exponential smoothing-based scheme to decrease the influence of the initial market conditions over long time periods.

3.3. Stochastic public policy proposal to mitigate the effects of the pandemic over time

As previously demonstrated, the pandemic impacted the Brazilian distribution electricity market and decreased the socioeconomic welfare produced by the market (particularly due to the high homologated tariffs). In this section, a long-term/sustainable public policy is proposed to mitigate the impact of the pandemic based on a stochastic optimization problem. The following optimization problem was designed and thoroughly thought to satisfy the interests of the market agents (power
distribution company and consumers) and government simultaneously, without the need for loans that harm consumers in the medium-/long-term:

Objective function:

$$\min |ECA_{NP} - ECA_{P}|$$

Design variables:

$$\mu_p, T_p$$

Subject to:

$$E_p = \frac{(a_p - T_p)}{b_p}$$

$$\mu_p \geq \alpha$$

$$T_p \leq \beta$$

$$P_x(EVA_x) \geq 0$$

where:

The index "NP" regards the non-pandemic simulation, i.e., parameters prior to the pandemic are used for simulation; The index "P" regards the pandemic simulation, i.e., parameters following the pandemic are used for simulation; Naturally, the regulatory agency/government only control variables/parameters with the index "P" (pandemic context), which is the current market situation; The objective function $$|ECA_{NP} - ECA_{P}|$$ seeks to minimize the pandemic's impact on the consumers' surplus, i.e., minimize the mean ECA difference between the non-pandemic simulation and the pandemic simulation (the absolute value is taken); The design variables are assumed to be the sales taxes ($$\mu_p$$) and tariff ($$T_p$$), i.e., it is assumed that the government can guarantee tax exemption by reducing the $$\mu_p$$ parameter and also that the regulatory agency can stipulate an intended tariff value; The parameters $$a_p$$ and $$b_p$$ are the avidity and satiety of the consumers, respectively (as defined in Eq. (2)); The constraint $$E_p = \frac{(a_p - T_p)}{b_p}$$ is related to the marginal utility concept, which is widely recognized in economics. This constraint is essential since a tariff modification implies consumption modification; The constraint $$\mu_p \geq \alpha$$ has the purpose of avoiding financial burden for the state/federal government ($$\alpha$$ is assumed to be a constant defined by the government); The constraint $$T_p \leq \beta$$ has the purpose of ensuring fair electricity tariffs for consumers ($$\beta$$ is assumed to be a constant defined by the government and/or regulatory agency);

$$P_x$$ denotes percentile, i.e., this constraint defines the certainty level of EVA being non-negative (e.g., $$P_{0.05}(EVA_x) \geq 0$$ denotes 60% probability of non-negative EVA). By setting a reasonable percentile, the regulatory agency can ensure a high likelihood of FEE for the power distribution company. It is important to emphasize that exaggerated percentiles inhibit practical solutions as they require excessive tariffs and/or low sales taxes.

Another possibility would be to assume $$\max(EVA_x)$$ as the objective function (maximize the socioeconomic welfare); however, this implies $$\mu_p = \alpha$$, which means that more tax exemption is being conceded than necessary to mitigate the impact of the pandemic (going against the proposal of being a sustainable policy).

In conclusion, the objective function and the constraint $$T_p \leq \beta$$ satisfy the interests of the consumers, the constraint $$P_x(EVA_x) \geq 0$$ satisfies the interests of the power distribution company, and the constraint $$\mu_p \geq \alpha$$ satisfies the interests of the government.

The optimization problem proposed in (10) must be applied for every time step (month). Although in Brazil, both $$T$$ and $$\mu$$ are fixed by ANEEL for the whole year, they are assumed to be set monthly so that the impact of the pandemic can be mitigated over time.

Finally, the proposed optimization problem can be applied to a Brazilian concession area to verify if it operates properly. The concession area of CPFL Paulista is analyzed from April / 2021 to Dec / 2021. The optimization engine implemented within Oracle Crystal Ball® (OptQuest) was used since it presents stochastic features such as percentiles. Fig. 19 presents how the tariffs and sales taxes vary over time to ensure market optimization, assuming $$\alpha = 20\%$$, $$\beta = 863.90$$ (MR$/TWh), and $$\lambda = 60\%$$. As expected, the proposed optimization problem tends to reduce both $$T$$ and $$\mu$$ to achieve market optimization. Particularly for CPFL Paulista (and for the assumed $$\lambda$$), the tax exemption would not be necessary following month 3. Fig. 20 demonstrates that the proposed technique increased the socioeconomic welfare of the market; thus, the results were satisfactory.

By performing multiple simulations with distinct parameters (information provided in the Appendix), the following conclusions were obtained regarding the behavior of the proposed optimization problem and what would be essential for it to be implemented in practice (along with philosophical discussions that are not necessarily related to the simulation results):

- In general, the optimal tariff does not vary abruptly monthly, i.e., the market is likely to remain stable. In contrast, Brazil’s current tariff review process usually results in sudden tariff variations of up to 30%. In addition, annual variations limit regulatory agency interventions. For instance, the tariff review occurred four months after the pandemic took place for the analyzed companies. While annual interventions have the advantage of reducing costs (the tariff review process is costly), they are not particularly satisfactory in the context of crises such as the COVID-19 pandemic, since when an unexpected event occurs that affects the electricity market, the costs involved will only be passed on to the consumer at the end of the review cycle, which takes months;

- The increasing behavior of the optimal tariff in Fig. 19 is due to the positive consumption growth tendency of CPFL Paulista following the pandemic, i.e., the increasing behavior occurred since data from [98] do not indicate that the consumption of CPFL Paulista was affected by the pandemic. Results demonstrate that the optimal tariff would present decreasing behavior if the pandemic reduced the consumption growth tendency (and the gap between the optimal EWA and the non-optimal EWA illustrated in Fig. 20 would widen over time). Therefore, the behavior of the optimal tariff is intuitive, as it tends to compensate the pandemic’s impact. In other words, the proposed public policy self-adjusts over time based on market trends. Mathematically, this occurs since $$ECA_{NP}$$ is used as reference;

- Two factors are of utmost importance to properly apply the proposed optimization problem: (i) the demand elasticity must be accurately estimated (stochastic approaches are expected to be superior to deterministic approaches) so that it is possible to forecast how consumption will change due to a tariff modification, (ii) consumption growth tendencies must be updated monthly, particularly since tariff modifications will intrinsically modify tendencies;

- To implement robust stochastic optimization techniques in the context of smart markets, advanced comprehension of the market’s conditions/aspects is required. For instance, the regulatory agency must be able to estimate how a public policy will modify seasonality. Moreover, while a general optimization problem was proposed in (10), it might be beneficial to take into account regional characteristics (9), e.g., the seasonality changes considerably depending on the concession area;

- A holistic view of the effects of public policies is always required, i.e., economic, social, environmental, and political aspects must be thoroughly assessed when implementing a public policy. For instance, a tariff modification might modify the demand for DG,
impacting the environment. While such holistic analysis is inherently challenging, it is of utmost importance for the further development of smart markets. Therefore, the continuous effort of the scientific community on the topic is essential to introduce holistic/robust smart markets optimization techniques.

Based on the conducted study and the philosophical discussions mentioned above, the following managerial insights are provided to enhance the recovery process of Brazil’s regulated electricity markets when undergoing periods of crisis such as the COVID-19 pandemic:

- ANEEL should carry out tariff review processes with a higher frequency, as annual processes limit the market’s flexibility and recovery measures;
- When implementing public policies, the government should focus on long-term/sustainable solutions, which do not introduce interest rates. This paper proved that it is possible to comply with the interest of all market agents and government simultaneously without introducing interest rates;
- Although the philosophy of the current regulatory framework is reasonable in Brazil (calculation of fair tariffs for consumers), ANEEL should gradually introduce more rigorous/robust techniques to enhance the calculation of the tariffs. Furthermore, this paper demonstrated that the pandemic’s impact varies significantly depending on the concession area, raising questions on whether a unified decision-making approach for the entire country is satisfactory;
- ANEEL should conduct in-depth electricity market studies for enhanced market intelligence. Data such as demand elasticities are essential for improved managerial decision-making;

While the above-mentioned improvement opportunities are authentic, the authors recognize that ANEEL currently works with limited resources, making the implementation of large-scale approach modifications challenging.

The managerial insights are provided based on Brazil’s reality since Brazil was the object of study in this paper. However, they might also be valuable for other countries/regions with characteristics similar to Brazil’s (e.g., limited economic growth pre-pandemic and containment policies post-pandemic).

4. Conclusions

The impact of the COVID-19 pandemic on humanity has been vast, justifying the apparent effort of the scientific community to mitigate it and identify emerging opportunities in the post-COVID-19 Era. However, there is an undeniable research gap on forecasting analyses of the pandemic’s impact on the electricity market from a socioeconomic point of view. Therefore, this paper seeks to fill such a gap and contribute to the development of more robust/rigorous methodologies for assessing electricity markets undergoing periods of crisis. In order to do so, the research separates monthly data from the Brazilian regulatory agency into two groups, i.e., prior and post-pandemic, and conducts time-series stochastic simulations of the pandemic’s impact by combining the optimized tariff model and random walk concept. The time-series stochastic simulations demonstrate an extensive pandemic’s impact on consumers due to the high validated tariffs following the pandemic (losses on the order of 132 (MR$/month) per concession area), and a nonexistent impact on distribution companies (profit on the order of 38 (MR$/month) per concession area). The value at risk calculation confirms that the pandemic’s impact on consumers is statistically significant, as the VaR(99.99%) is equal to 1.16%, i.e., virtually all iterations were impactful. Given the substantial pandemic’s impact on consumers, a novel stochastic optimization problem (public policy) is proposed to mitigate it. Results demonstrate it is highly effective as it self-adjusts over time to compensate for the pandemic’s impact. Furthermore, the interests of consumers, distribution companies, and the government are simultaneously assured, making it a fair policy.

Some potential extensions are acknowledged. First, although the applied forecasting technique (random walk with seasonality components) proved to present satisfactory accuracy while limiting complexity, it might be beneficial to apply other forecasting techniques in future research (e.g., ARIMA, Holt-Winter’s method, artificial intelligence). Second, developing a deregulated socioeconomic market model in future research is certainly beneficial, as the optimized tariff model is typically applied in the regulated environment. Therefore, a deregulated socioeconomic market model would expand the applicability of the study.

CRediT authorship contribution statement

Vinicius B.F. Costa: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. Lígia C. Pereira: Conceptualization, Resources, Data curation, Writing – original draft, Writing – review & editing. Jorge V.B. Andrade: Conceptualization, Writing – review & editing. Benedito D. Bonatto: Resources, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A Concession areas

Table A1 describes the model’s MAPE concerning electricity consumption. As verified, the MAPE is equal or lower than 3.41% for all concession areas, implying the proposed model satisfactorily represents the data. Table A2 describes additional information from the concession areas analyzed in this paper for better contextualization. Tables A3-A6 describe the input data used in the simulations. Based on Tables A3-A6, results can be replicated.

Appendix B Additional simulations/optimizations

Besides the simulations/optimizations conducted in Section 3.3, we also conducted a series of optimizations for the concession area of CPFL Paulista (public policy proposed in Eq. (10)), assuming a monthly growth tendency of -0.30% for the electricity consumption post-pandemic, i.e.,
assuming a hypothetical scenario where the pandemic significantly decreased CPFL Paulista’s electricity consumption. All other parameters were assumed to be equal so that the results represent only the effects of a negative consumption growth tendency. The results are presented in Fig. B1. As verified, the public policy tends to decrease the tariff to compensate for the decrease in electricity consumption. Fig. B.1 also illustrates that the tax parameter tends to decrease due to the reduction in the company’s revenue caused by the downward optimal tariff trend. Therefore, Fig. B.1 illustrates a distinct pattern to that previously presented in Fig. 19 (where a positive consumption growth tendency was assessed).

In conclusion, if the pandemic leads to a reduction in electricity consumption, the optimal tariff and the optimal $\mu$ parameter tend to decrease over time (Fig. B.1). In contrast, if the pandemic does not lead to a reduction in electricity consumption, the optimal tariff and the optimal $\mu$ parameter tend to increase over time (Fig. 19). Therefore, the proposed public policy operates satisfactorily as it tends to compensate for the pandemic’s impact.

The logic presented in the last paragraph is valid for any concession area. In order to demonstrate so, the results of applying the proposed public policy for Energisa SE are illustrated in Fig. B2. The electricity consumption growth tendency of Energisa SE is virtually the same pre/post-pandemic; thus, Fig. B.2 illustrates a practically constant tariff. Energisa SE does not require tax exemption for $\lambda = 60\%$. 

![Fig. B1. Alternative application of the proposed public policy for the concession area of CPFL Paulista.](image1)

![Fig. B2. Application of the proposed public policy for the concession area of Energisa SE.](image2)
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