PRICING FOR DISTRIBUTED ENERGY RESOURCES

Marcio Andrey Roselli (Lead Author), André Luiz Veiga Gimenes, Miguel Edgar Morales Udaeta and Eduardo Crestana Guardia

2023 ICER Distinguished Scholar Awards

The Energy Transformation Challenge: Competitiveness and Sustainability of Energy Markets, Opportunities, and Achievements

November 28, 2022

EXECUTIVE SUMMARY

The objective of this work is a specific model of network tariffs for Distributed Energy Resources using loss spectrum marginal cost pricing considering energy demand response. The model uses data from customer load profiles, distribution networks, and associated standard costs. The loss spectrum marginal cost pricing uses the loss responsibility model, i.e., the increase in losses on the elements of the whole network due to the marginal increase in customer load. The loss responsibility model is adapted to weigh the influence of load profile on the maximum network losses, maintaining the thermal balance of the system in a long-term expansion paradigm. We adjusted the marginal revenues to be compatible with the regulatory costs, following the causality criteria and financial requirement. Our analyses are applied to the Distribution System, with about 200 thousand customers. We examine the economic impact of Battery Energy Storage Systems, Rooftop Photovoltaic System, and Electric Vehicle Recharging. This article studies the relation between Distributed Energy Resources, and the impact of the cost in distribution network and tariffs.

Electricity tariffs are the main driver of the behind-the-meter adoption of Distributed Energy Resources, inducing dispatch and drastically changing the netload in the distribution network (Heleno et al. 2020a). Hence, it is necessary to implement policies to encourage Distributed Energy Resources, such as time-varying pricing (Ansarin et al. 2020) or locational cost analyses (F. Sioshansi 2020). The fixed network is shared with a few customers, which increases the volumetric charge per consumers. It is called the distribution Death Spiral, i.e., continuously customers adopt Distributed Energy Resources systems due to progressively rising retail prices. Overall, customers pay the costs of capacity services on a volumetric basis, which results in an increasing share of capacity costs by customers without Distributed Energy Resources (R. Sioshansi 2016). In addition, flat tariffs increase electricity bills, peak netload, and fail to allocate reliability system costs (Fridgen et al. 2018). Suddenly, network tariff design has become a concern (Schittekatte, Momber, and Meeus 2018).

Thus, to address this problem, this paper contributes to the literature by presenting a methodology to quantify the network costs impact due to Distributed Energy Resources and set an associated electricity tariff on the long-run marginal cost paradigm. We follow

the usual tariff criteria by the Distribution System Operators and regulatory entities. Hence, the contributions of this paper are threefold:

- First, to perform an analysis considering the regulatory process to construct a specialized network tariff for Distributed Energy Resources. For this purpose, we used the cost-reflective tariff, Pareto optimality, and financial requirement.
- Second, to propose a model that uses Long-Run Marginal Costs criteria for the network tariffs, according to the regulatory process.
- Finally, to propose a model that uses a real system with thousands of elements and customers to consider a charge diversity to peak-load pricing.

Consumers are traditionally divided into limited customer groups, due to homogeneous elasticity characteristics and consumption habits. The consumer classes met the requirements of the tariff structure of the distribution electricity systems. However, the characteristic of investment capacity in Distributed Energy Resources must be considered in the evolution of the current tariff structure. There are no off-the-shelf models for the tariff structure, i.e., they must be evaluated on a case-by-case basis, according to the technical, economic, and social characteristics of the area.

However, cost causation criteria, financial requirement, and tariff stability must be considered when setting the tariffs for the new kind of standard customers. Thus, more accurate tariff structure models should be used to evaluate the economic impacts due to the variability of the characteristics of consumers, besides changing their consumption behavior through automation and electric vehicle recharging, and investment in energy storage and production.

The findings presented in this paper emphasize the importance of Distributed Energy Resources tariff structure to make explicit the marginal and average costs per customer. The model substantially increases the calculation precision of impact costs and tariff, which enables statistical analysis of regionalized data and by customer characteristics, i.e., leaving it up to regulatory entities to define tariff structure.

The Pareto optimal tariff is applying for Rooftop-PV. Our results indicate that it varies due to the load profile, and it is advisable to employ at least one differentiated tariff by consumer class. The findings presented in this paper emphasize the importance of a tariff structure that includes periods of optimal distribution network cost for Battery Energy Storage Systems in peak shaving. However, for the correct signaling, it is necessary to

reduce the temporal and locational granularity. The findings presented in this paper emphasize the importance of locational and dynamic price, indicating the best benefits of installing Battery Energy Storage Systems for peak shaving and sharing efficiency gains.

The findings presented from Battery Energy Storage Systems can be applied to Electric Vehicle Recharging. Furthermore, there is a high price response because there will be no disconformity in changing the load profile. Thus, there will be a substantial increase in the consumption price elasticity, reducing the market response.

The model is consistent, and it ensures a holistic tariff model to Distributed Energy Resources. Our analyses reveal an average tariff of 154.98 $/MWh for Smart Charging for charging time of 8 hours, against one of up to 265.77 $/MWh for Uncontrolled Charging. Moreover, with the application of locational tariffs by identifying the 10% of customers with the highest Economic Benefit and a 2-hour discharge period, it is possible to obtain an Economic Benefit of $ 333.51 per kWh injected into the distribution network.

The tariff structure chosen is essential for a fair and efficient distribution system with vast Distributed Energy Resources adoption. The proposed model can offer more cost causality criteria designs by reducing temporal and locational granularity, which would allow studying the impact of the Distributed Energy Resources in tariff structure.

PRICING FOR DISTRIBUTED ENERGY RESOURCES

Marcio Andrey Roselli[1, 3, *], André Luiz Veiga Gimenes[2], Miguel Edgar Morales Udaeta[2], Eduardo Crestana Guardia[1]

[1] Institute of Electrical Systems and Energy of Federal University of Itajubá, Av. BPS, n°1303, Pinheirinho, Itajubá, Brazil
[2] Energy Group of Department of Energy and Electrical Automation Engineering of the Polytechnic School, University of São Paulo, Av. Professor Luciano Gualberto, Travessa 3, n° 158, Prédio da Engenharia Elétrica, São Paulo, Brazil
[3] Brazilian Electricity Regulatory Agency, SGAN 603 Modulo J, Brasília, Brazil
*marcio@unifei.edu.br

Key words: Network Tariffs; Tariff Structures; Distributed Energy Resources; Distribution System Operators.

1. INTRODUCTION

Practical aspects of regulation, concepts of justice, and equity resulted in the current theoretical foundations of tariff design (DORAU 1930). In the behind-the-meter paradigm, customers invest in Distributed Energy Resources (DER). They have adopted Battery Energy Storage Systems (BESS), Rooftop Photovoltaic Systems (Rooftop-PV), and Electric Vehicle Recharging (EVR) in response to price signals given by the network or by the market (Blackhall et al. 2020). In addition, the customer has access to communication at a low cost, and, as a result, their load profile is more responsive to the price. In the beyond-the-meter paradigm, Distribution System Operators (DSO) planning becomes more complex, considering that decisions of expansion in network capacity and generation are not centralized (Lazar et al. 2017; COHEN 2017).

The new technologies increase price elasticity, enabling modulation and increased network efficiency. Nowadays, the energy flow is bidirectional, elasticity increases, and customers invest in energy production, reliability, and network capacity. Henceforth, low-voltage customers cannot be considered passive anymore because Rooftop-PV enables consumers to self-produce energy. In addition, BESS enables self-producers to choose both their network energy and capacity parameters (Schittekatte, Momber, and Meeus 2018).

Electricity tariffs are the main driver of the behind-the-meter adoption of DER, inducing dispatch and drastically changing the netload in the distribution network (Heleno et al. 2020a). Hence, it is necessary to implement policies to encourage DER, such as time-

varying pricing (Ansarin et al. 2020) or locational cost analyses (F. Sioshansi 2020), e.g., Germany and Denmark are subsidizing network reinforcements due to Rooftop-PV and the lack of a refined price signal transmission (Anaya and Pollitt 2015).

The flat-rate tariffs show significant cross-subsidization from consumers to prosumers (Garfield and Lovejoy 1964). The deployment of DER heavily increases Distribution Network Tariffs (DNT) to residential customers, especially under price-cap regulation, which assumes continuous load growth (el Hage and Rufín 2016).

The fixed network is shared with a few customers, which increases the volumetric charge per consumers. It is called the distribution Death Spiral, i.e., continuously customers adopt DER systems due to progressively rising retail prices. Overall, customers pay the costs of capacity services on a volumetric basis, which results in an increasing share of capacity costs by customers without DER (R. Sioshansi 2016). In addition, flat tariffs increase electricity bills, peak netload, and fail to allocate reliability system costs (Fridgen et al. 2018). Suddenly, network tariff design has become a concern (Schittekatte, Momber, and Meeus 2018).

Several factors influence the tariff structures, such as causality criteria, financial requirements, and fairness (Moncada et al. 2021b). However, DER policy and economics neglect the influence of social and behavioral components on decisions (Yakubovich, Granovetter, and Mcguire 2005). Hence, Regulatory entities that have suffered greatly with this issue have reacted by limiting, rescinding, or eliminating incentive programs for DER (R. Sioshansi 2016).

Conceptually, the cost causality criteria can be met by using temporal and spatial granularity to the network tariff model, which would allow studying the economic impact of DER on distribution, energy losses, and tariff structures. Likewise, the tariff design chosen is essential for a fair and efficient distribution system with massive DER adoption (Bustos, Watts, and Olivares 2019).

Price signals should be cost-reflective so that DER operation aligns with the optimal system-wide utilization of assets. However, understanding cost-reflective is becoming more complex, especially due to the structural changes in the planning and operation of the distribution network (Blackhall et al. 2020).

The way DSOs have been recovering their costs through tariffs needs reformulation. The penetration of DER within the distribution network directly affects how DSOs charge

their customers a fair and cost-reflective tariff. Therefore, the new and adjusted tariffs impact innovation acceptance, evidencing a clear feedback loop (Freitas Gomes, Perez, and Suomalainen 2021; Heleno et al. 2020b; S. P. Burger et al. 2020). Amendments to tariff design are one of the main tools for expanding the benefits of customer engagement and DER assumption.

The marginal costs of DER are nearly achieving the production, transport, and quality of the distribution network cost (Initiative 2016). Consequently, parameters for comparing tariffs through indirect competition emerge, making sectoral inefficiencies explicit. The cost-reflective tariff becomes evident and sectoral subsidies become explicit (Schramm 1985a). Thus, computational models for pricing energy transportation will be increasingly demanded (Papavasiliou 2018).

There is a practice in welfare economics that suggests that prices should be based on Long-Run Marginal Costs (LRMC) to achieve economic efficiency. Nevertheless, network revenue constraints are often based on embedded costs, typically superior to LRMC, which creates the problem of recovering residual costs (Brown, Faruqui, and Grausz 2015).

Economic analyses with a behind-the-meter approach are applied in Rooftop-PV (Sharma, Han, and Sharma 2019; Hayat, Shahnia, and Shafiullah 2019), BESS (Barcellona et al. 2018; Koskela et al. 2019; Biroon, Biron, and Hadidi 2020), or EVR (Chekired, Khoukhi, and Mouftah 2018). Furthermore, the economic value of coordinating the planning, operation, and procurement of DER, is presented (Carvallo et al. 2020). They demonstrate how a DSO could largely overcome the complications of DER decision-making by incentivizing regulatory bodies to develop electricity tariffs that more closely reflect time and location, in an LRMC paradigm (S. P. Burger et al. 2020). According to (Carvallo et al. 2020), the decisions to invest in DER do not originate from any coordinated planning effort, and the decisions to operate these resources do not respond to any coordinated dispatch process. Nevertheless, in this paper, network tariff is an independent or exogenous variable.

The paper (Moncada et al. 2021a) focuses on assessing the impact of possible tariff designs on DERs adoption and the DSOs death spiral, rather than investigating what an optimal tariff should look like. They developed an agent-based model to evaluate the interaction between tariff design and DER. In Ref. (Schittekatte, Momber, and Meeus 2018), the genera cost recovery problem for the DSO is modeled as a non-cooperative

game between consumers, i.e., the availability and costs of the technologies strategically interact with tariff design. Depending on the tariff design, customers can offset their contribution from the failed network costs by investing in DER. Likewise, in this paper, the tariff is an independent or exogenous variable.

Conversely, in a Short Run Marginal Costs (SRMC) paradigm, there is a group of methods that uses the Distribution Locational Marginal Prices (DLPM) model to calculate the energy price considering network contingency costs (Rana and Mishra 2019; Zhang et al. 2019; Papavasiliou 2018). ERV is highly responsive to the price signal. Therefore, it is common in this type of research to adopt DLPM for time-varying pricing, as demonstrated in (Ghosh and Aggarwal 2017; Wang et al. 2018; Zheng et al. 2019). The goal is to calculate the energy cost considering the SRMC of the distribution network and propose a model that contributes to the network efficiency using the price signal.

The DLPM involves modeling thousands of devices and modeling DER complexity (Kraning et al. 2013). However, this research does not cover the totality of DSO networks. Most of these proposals are conceptual and lack strictness and details in distribution market operations analysis, demanding an investigation of the regulatory and institutional processes (Parhizi and Khodaei 2016).

Conceptually, in terms of average expectation, LRMC is equivalent to a combination of SRMC and the optimal investment rule (Turvey 2017). Nevertheless, high price variations are not tolerated by customers, especially when it comes to public utilities, i.e., tariffs must be politically and socially acceptable (S. Burger et al. 2019). Hence, economic, and political considerations would rule out the implementation of SRMC (Schramm 1985b). The problem with price fluctuations is avoided with the LRMC.

This study explores a model that provides locational and temporal marginal cost signals, offering support for the decision of regulatory entities and DSO to DER regulation, as the need mentioned in the (O'Shaughnessy and Ardani 2020). The main factor in cost causality criteria is the granularity of DNT. This paper focuses on assessing an optimal DER tariff, using beyond the meter analysis. Thus, to address this problem, this paper contributes to the literature by presenting a methodology to quantify the network costs impact due to DER and set an associated electricity tariff on the long-run marginal cost paradigm. We follow the usual tariff criteria by the DSO and regulatory entities. Hence, the contributions of this paper are threefold:

- First, to perform an analysis considering the regulatory process to construct a specialized network tariff for DER. For this purpose, we used the cost-reflective tariff, Pareto optimality, and financial requirement.
- Second, to propose a model that uses LRMC criteria for the network tariffs, according to the regulatory process.
- Finally, to propose a model that uses a real system with thousands of elements and customers to consider a charge diversity to peak-load pricing.

This paper proposes a new model of dynamic and locational electricity distribution network tariffs to DER, demonstrating the feasibility of defining a cost-reflective tariff, following cost causality criteria. In the following pages, we first review background literature on electricity distribution network tariffs. Section 3 covers details on dynamic and locational tariffs methodology, using the loss spectrum marginal cost pricing model, according to (Roselli 2020). In Section 4 the model covered in Section 3 is applied in a distribution network with DER to get a specific analysis of the tariff structures of BESS, Rooftop-PV, and EVR. Finally, Section 5 presents the conclusions of the paper.

2. TARIFF STRUCTURES

2.1. Marginal Costs Criterion

The first stage of tariff structures is the calculation of strict LRMC that considers the economic efficiency criterion (Schramm 1985b). According to (Turvey 2017), LRMC is the present worth of all system costs as they will be with the increment in load, which is to be costed, less what they would be without that increment. If the price was set equal to LRMC, consumers could indicate their willingness to pay for more energy, thus justification for further investment to expand capacity. In the second stage of tariff design, we sought ways in which the LRMC may be adjusted to meet the other objectives, among which the financial requirement is the most important, i.e., producing revenues approved by the regulatory entities (Munasinghe 1981).

The marginal costs tend to be higher than average costs when the unit costs of supply are increasing. Hence, if prices were set equal to LRMC, it is likely that there will be a financial surplus. Conversely, if marginal costs are below average costs, the pricing at the

LRMC will lead to a financial deficit. Thus, a general price increase will be necessary for the financial requirement criterion.

Another reason for diverging from the LRMC arises because of the second-best policy. The tariff structure must recognize various electric energy substitutes and complements (Munasinghe 1981). The goal of the Electricity Distribution Network is to grow, even if it means making it prevent excessive use of the alternative forms of energy. In this case, pricing electricity below the LRMC may be justified (Munasinghe 1981; Caywood 1972; Schramm 1985b). Nevertheless, tariff design is against unfair discrimination. According to (Nash 1933): *"[...] discrimination is commonly understood to mean a difference in rates or service conditions relating thereto for service of substantially the same characteristics, taking into account volume, load factor, load density, time of use, character of use, and any other significant factors"*. Thus, the discrimination of DNT has been admitted if it respects measurable parameters.

2.2. Peak-Load Pricing and Customer Responsibility

In 1892 John Hopkinson created the two-part tariffs for electric energy distribution, explicitly considering maximum demand and power consumption as independent calculation bases for the electric energy costs (Garfield and Lovejoy 1964). A conceptual model of peak-load pricing was proposed by Steiner (Steiner 1957). For the optimal prices, in peak periods, settings tariffs to long-run marginal cost, and when there is idle capacity, i.e., off-peak periods, setting tariffs to system marginal running cost (Simshauser 2016). Furthermore, a peak capacity-based tariff is a more efficient, cost-reflective, equitable, and improves the tariff stability, providing a financial requirement (Simshauser 2016). With the metering evolution, peak load pricing adopts the period of occurrence. The energy rates would be the generation cost itself. The example proposed in Fig. 1 presents a distribution system with three customers, the transformer to which they are connected, and the respective load profiles. The objective is to divide the transformer costs exclusively.

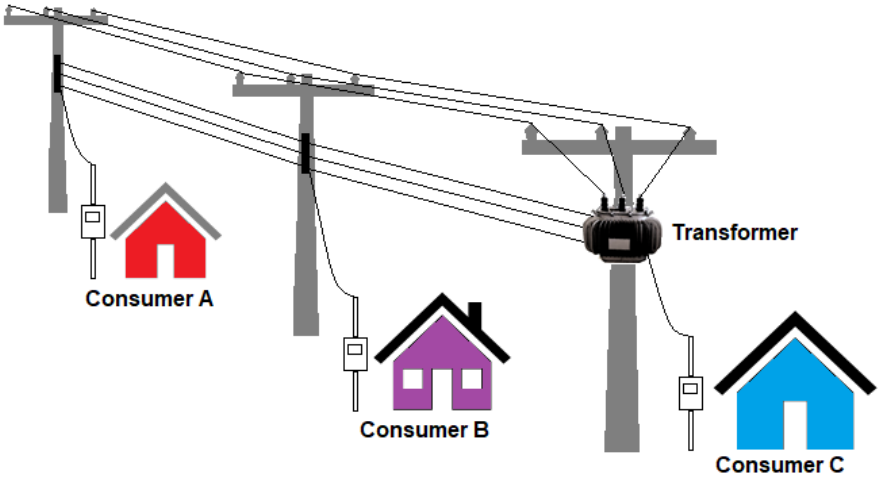

Fig. 1a. Consumer Unit.

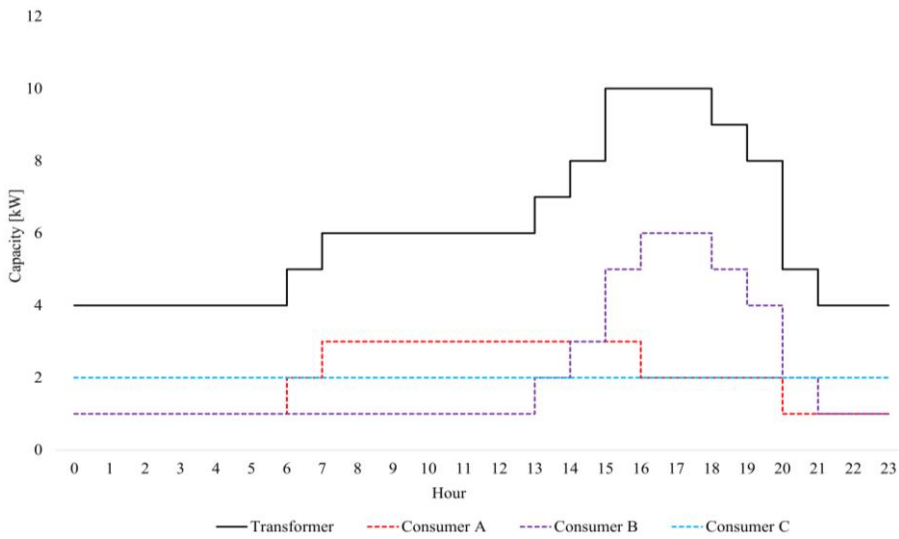

Fig. 1b. Load Profile.

When disregarding the losses in the low voltage network, branch line, and meter, the transformer peak occurs at 5 p.m., with a demand of 2kW for customers A and C and 6kW for customer B. Considering that the expansion is due to maximum netload, it is reasonable to apportion the costs of the equipment to the contribution, or responsibility, of the customer at the transformer peak time. This way, the customer's A and C contribution to the expansion would be 20%, and for customer B 60%, which would be the basis for the collection of the tariff share referring to the system expansion, based on the incremental transformer cost ($/kW).

Some model criticisms presented should be pondered considering the tariff criteria. Firstly, the final energy cost can be erratic due to unpredictable load profile variation or customer apportionment. In second place, for some customers, load modulation may be

unfeasible, and the economic signal is innocuous, which would impair customer acceptance (Biggar 2010). Thirdly, considering that the expansion will occur exclusively due to the peak is a simplification that disregards the load dynamics and transformer thermal models. The load condition in off-peak time influences the capacity supported by the transformer. Finally, in the practical case, the load profile presented is a static representation. However, the load profile tends to vary according to the day of the week and has seasonal variation. For these reasons, we search for a comprehensive model that can be attributed to customers for the expansion costs.

When considering the LRMC criterion the optimal investment rule is assumed. Therefore, the idle capacity of the transformer is necessary for the operation and should be apportioned among all consumers, i.e., the costs of a transformer should be apportioned according to the peak load usage. In contrast, if we consider the SRMC criterion for apportioning network costs, then the marginal cost of using the transformer is zero (losses are ignored). The SRCM criterion would cause erratic tariff variations, impairing the financial planning of customers and DSO (Brandstätt, Brunekreeft, and Friedrichsen 2011).

3. LOCATIONAL AND DYNAMIC DISTRIBUTION SYSTEM TARIFF

The purpose of this item is to present a problem-solving approach, applied to a distribution system with thousands of modellable elements that considers long-term cost pricing, following cost causality criteria and financial requirement. The lack of comprehensive models that consider tariff criteria inhibits the evaluation of the economic influence of DER.

3.1. Losses Spectrum Marginal Cost Pricing

This paper proposes an evolution in the proposed method presented in (Roselli 2020). The model results in locational time-varying pricing, as described in the following topics.

3.1.1. Losses Responsibility

Conceptually, the peak-load capability is the main driver of the network costs. Several models present the peak-load capability as a function of constructive conditions, ambient temperature, and network element losses (Li et al. 2005; Alvarez, Rivera, and Mombello 2019). Therefore, we can extend the model to include the peak-load capability depending on losses, keeping the assumption of invariability of ambient temperature.

As defined in (Queiroz et al. 2012), the loss resulting from a load variation, is given in Eq. (1).

$$Losses = Losses_{flat}.(CV^2 + 1) \tag{1}$$

According to Eq. (1), *Losses* are the equivalent *Loss*es resulting from mean current *I(t)* transmission (*flat*) in an element of a network, multiplied by the current curve statistical Coefficient of Variation (*CV*) squared. In nominal conditions and steady-state, Ref. (Queiroz et al. 2012) adopts the power per unit equivalent to current, which leads to the active power load profile CV.

As defined in (Roselli et al. 2022), when considering the root-mean-square wave, the losses are given by Eq. (2). Where H_i is the sine/cosine amplitude function and H_0 is the average power demand profile. Therefore, we can calculate the periodic wave variance by half the sum of squared amplitudes of its harmonics.

$$Losses = Losses_{flat} \cdot \left(\sum_{i=1}^{N} \left(\frac{H_i}{H_0}\right)^2 + 1\right) \tag{2}$$

Each load harmonic component contributes to the loss composition. The harmonic amplitude squared defines the loss spectrum. With new technologies such as DER, consumers become prosumers (Bustos, Watts, and Olivares 2019). The loads now lean for a bidirectional flow, changing the load profile, mainly during the day due to Rooftop-PV. The model proposed by (Roselli et al. 2022) generalizes the load profile, allowing the negative representations of peak. Figure 2 presents a typical transformer daily netload profile and curve with a low pass filter, considering only up to its octave order.

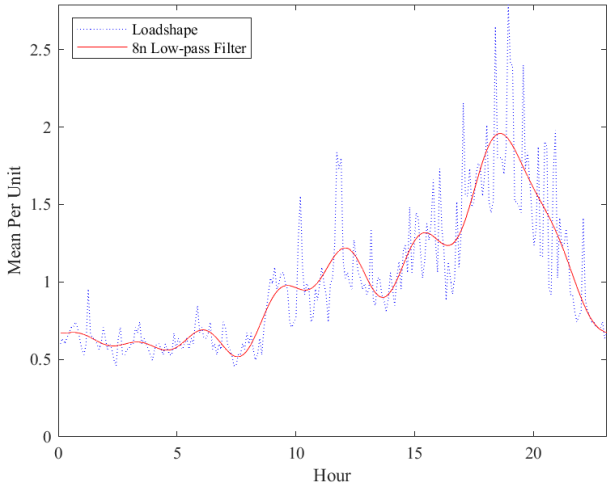

Fig. 2. Transformer daily load profiles Low-pass filter.

We chose the harmonic order of 8n according to the identification of significant harmonic components and random fluctuations based on Whittle´s tests (Roselli et al. 2022). The representation approaches the curves as we reconstruct the load profile by higher harmonic orders. Even using all harmonic orders, the sampling frequency limits (Nyquist rate) the curve accuracy. The load profile representation in the frequency domain conceptually has advantages over the time domain. Firstly, there is the decay of harmonic order modules, e.g., with 15,000 transformer daily load profiles, normalized by continuous component unit, we obtained the curve of streaks (harmonic spectrum) in the form of a boxplot, see Figure 3.

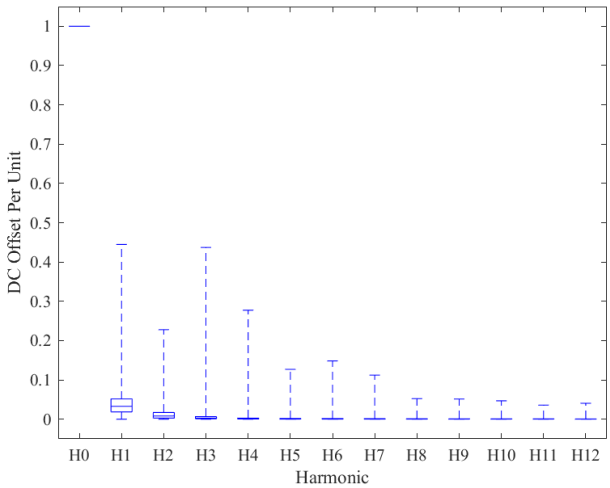

Fig. 3. Harmonic spectrum of transformer daily load profiles.

Second, the module reduction is inversely proportional to the harmonic order (see Figure 3). This feature is desirable because we can prioritize components in simplifications of

load models. There is a low variance in the model in the frequency domain (see Figure 3). This characteristic demonstrates the convenience of using the frequency domain information to collect patterns in load profiles.

The variation of losses of network element *j*, due to a load variation of customer *k*, can be obtained by the derivative of the Eq. (2) for each load harmonic *i*, i.e., $(\partial\, Losses)/(\partial\, H_i\,)$. According to (Roselli 2020), the model assumes that when increasing the load of a customer *k*, assuming load profiles are constant, the incremental losses in network element *j* to which it is connected are due to the Loss Responsibility ($LR_{\,j,k}$) Eq. (3).

$$LR_{j,k} = \frac{1}{{P_{base,j}}^2} \cdot \left(\begin{bmatrix} 1/H_{0,1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1/H_{0,k} \end{bmatrix} \times \begin{bmatrix} H_1 . H_{1,1} & \cdots & H_i . H_{i,1} \\ \vdots & \ddots & \vdots \\ H_1 . H_{1,k} & \cdots & H_i . H_{i,k} \end{bmatrix} . \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} + 2 . H_0 \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \right) \tag{3}$$

Where $H_i \cdot H_{i,k}$ represents the vector product between load harmonic *i* of network element *j* concerning load harmonic *i* of customer *k*. $H_{0,k}$ and H_0 represent, respectively, the average power demand profile of consumer *k* and network element *j*. We adopt the 24-hour fundamental of load harmonics. P_{base} represents the network element *j* nominal power rating. By concatenating the matrices $LR_{\,j,k}$ according to the connections of the network and load elements, it is possible to obtain the variation in losses in each distribution system element due to the customer *k* load variation.

Consider the example in Figure 1. By applying the Discrete Fourier Transformer (DFT), the load profiles of Figure 4 are obtained.

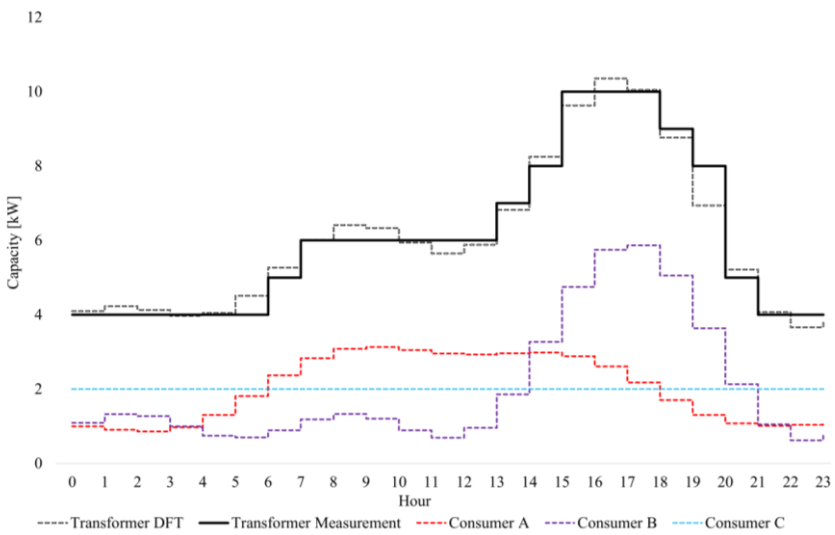

Fig. 4. Load Profile Low-pass filter.

Consider the transformer expansion cost apportionment model of Figure 1 applied to a transformer with the following data: power of 12.5 kVA, Copper Losses are 500 W and Iron Losses are 100 W. Consider unity power factor and 24 hours period (angular frequency $\omega = 2.\pi/24$). Table 1 presents the functions of the customer load profiles.

Table 1. Load profile

Load	Demand [kW]
A	$2.00 + 1.20 \cdot \cos(\omega.t - 2.92) + 0.15 \cdot \cos(2 \cdot \omega.t + 1.71) + 0.19 \cdot \cos(3 \cdot \omega.t + 0.53)$
B	$2.00 + 1.83 \cdot \cos(\omega.t + 2.09) + 1.28 \cdot \cos(2 \cdot \omega.t - 2.12) + 0.65 \cdot \cos(3 \cdot \omega.t - 0.05)$
C	2.00
Transf.	$6.00 + 2.46 \cdot \cos(\omega.t + 2.57) + 1.17 \cdot \cos(2 \cdot \omega.t - 2.20) + 0.82 \cdot \cos(3 \cdot \omega.t + 0.08)$

In addition, consider the transformer installation cost as being $ 3,000, with operation and maintenance costs of 2% per year and a remuneration rate of 5% per year. Converting the sine functions to rectangular complex form has the matrix that relates the harmonic components (Column) to consumers (Row), according to Eq. (1), is obtained in the complex matrix Eq. (4).

$$\begin{bmatrix} -1.17 - 0.27j & -0.02 + 0.15j & 0.17 + 0.10j \\ -0.09 - 1.59j & -0.67 - 1.09j & 0.65 - 0.03j \\ 0.00 + 0.00j & 0.00 + 0.00j & 0.00 + 0.00j \end{bmatrix} \quad (4)$$

As well as the vector that represents the harmonic components of the transformer, according to Eq. (5).

$$[-2.07 + 1.32j \quad -0.69 - 0.94j \quad 0.82 + 0.06j] \quad (5)$$

Applying the scalar product between Eq. (4) and Eq. (5) we have Eq. (6).

$$LR = \frac{0.5}{12{,}5^2}\left(\begin{bmatrix} 2^{-1} & 0 & 0 \\ 0 & 2^{-1} & 0 \\ 0 & 0 & 2^{-1} \end{bmatrix} \times \begin{bmatrix} 1.17 \cdot 2.07 - .27 \cdot 1.32 & .02 \cdot .69 - .15 \cdot .94 & .17 \cdot .82 + .10 \cdot .06 \\ .09 \cdot 2.07 - 1.59 \cdot 1.32 & .67 \cdot .69 + 1.09 \cdot .94 & .65 \cdot .82 - .03 \cdot .06 \\ -.00 \cdot 2.07 + .00 \cdot 1.32 & -.00 \cdot .69 - .00 \cdot .94 & .00 \cdot .82 + .00 \cdot .06 \end{bmatrix} \times \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 2 \cdot 6 \\ 2 \cdot 6 \\ 2 \cdot 6 \end{bmatrix}\right) \quad (6)$$

Solving Eq. (6), we now have Eq. (7).

$$LR = \begin{bmatrix} 4.172\% \\ 4.799\% \\ 3{,}840\% \end{bmatrix} \quad (7)$$

The transformer has the loss increased by 0.04172 kW, 0.04799 kW, and 0.0384 kW for a 1 kW increase in the load of customers A, B, and C. Obtaining the loss relativity impact for the consumer does not require knowledge about the equipment data. In addition, according to (1), the non-existent load harmonic components in the transformer do not contribute to the increase in losses. It is a useful characteristic in the simplification of calculations, according to Eq. 3.

Performing the loss simulation under operating conditions gives an average loss of 0.228109 kW. When customer A is marginally increased by 1 W, the loss will be 0.228151 kW, which represents a percentage increase of 4.172%, equivalent to the loss responsibility of customer A. As we will see next, the LR can be a useful tool for capacity definition and calculation of the marginal cost.

3.1.2. Time Loss Spectrum Marginal Cost Pricing

As proposed by (Steiner 1957), LRMC should be allocated only at the price peak. However, using the model of the thermal dynamics of electrical equipment, certainly the load condition in the off-peak period influences the system peak. When considering the power, for a two-stage curve, the initial condition taken as the off-peak stage will influence the peak approximately according to function f , Eq. (8) (Roselli 2020).

$$f = \frac{-\tau \cdot ln(1-k^2)}{T_P} \tag{8}$$

Where k is the ratio between off-peak and peak load, τ is the equipment thermal constant, and T_p is the peak duration. Note that for load factors close to unity there will be a large influence of off-peak load on peak period. The Eq. 8 applied to Figure 1 is shown in Figure 5 in comparison with the model proposed by (Steiner 1957).

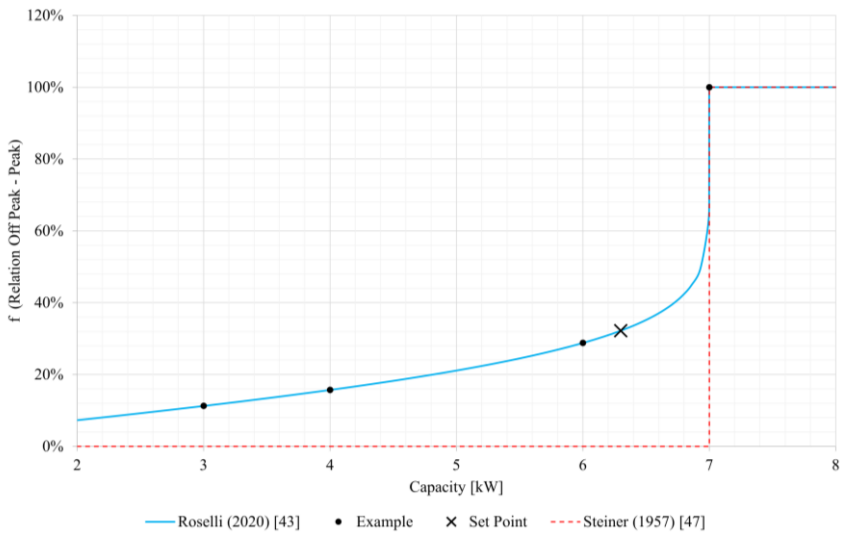

Fig. 5. Relation off Peak – Peak.

The setpoint is previously defined as a statical load profile percentile, which segregates peak and off-peak. By choosing the setpoint, we eliminate the need to define τ and T_p. The y-axis represents the total cost percentage. The losses by themselves do not define

the increase in the capacity of the electric system, but it is also defined by the moment of its occurrence. Therefore, before using Eq. (3) it is necessary to apply Eq. (8) to the customer's load profiles and transformers $C_k\ (h)$ and $C_j\ (h)$, respectively, which results in Eq. (9) and Eq. (10).

$$\{H_{1,k}, \dots, H_{i,k}\} = \mathcal{F}\{f(C_k(h))\} \quad (9)$$

$$\{H_1, \dots, H_i\} = \mathcal{F}\{f(\sum_{j=1}^{k} C_j(h))\} \quad (10)$$

Where $\mathcal{F}\{\cdot\}$ is the DFT. To maintain the thermal equilibrium conditions of an electrical distribution system, it is considered that the expansion will be proportional to the marginal increase in losses, qualified by Eq. (8). If the setpoint chosen is near zero, the model of Ref. (Steiner 1957) and Ref. (Roselli 2020) become equivalent. In this case, it is enough to apply Eq. 3 for the peak period, i.e., it is unnecessary to apply Eq. (8)-(10).

Thus, with $LR_{j,k}$, it is possible to obtain the Marginal Cost Pricing (MCP) of customer k according to (11) (Roselli 2020).

$$MCP_{k,j,h} = 0.5 \cdot LRMC_j(i_{O\&M}, i_{WACC}) \cdot f(LR_{j,k}) \quad (11)$$

Where: $MCP_{k,j,h}$: Marginal Cost Pricing of customers k, to element j *in the analyses* in period h; $LRMC_j$: LRMC of network j; $i_{O\&M}$: percentage of O&M Cost; and i_{WACC}: return rate of assets. The costs with distribution and transmission assets and operating costs will be prorated according to the *MCP* of consumer k (5). The costs with losses are apportioned according to the incremental share in the electric system losses according to (3).

3.1.3. Data Analysis

For the completeness of customer economic analysis on the network, it is necessary to adopt a standard load profile of the customer. Afterward, they are converted to the frequency domain using the DFT (Lee and Girgis 1988). The LRMC process is segregated by the municipality. The second dataset is the connection information between customers and network elements obtained from a georeferenced database.

3.1.4. Calculation Algorithm

The following algorithm is executed:

1. Load flow considering the load profiles.
2. Definition of network element peak by calculating the upper decile load profile.
3. Application of Eq. (8) on the customer load profiles and netloads and application of Eq. (9)-(10).
4. *LR* matrices calculation, according to (3).
5. MCP of customer to system elements by applying (11).
6. Marginal Revenue Calculation.
7. Sum of marginal revenues and adjustment factor for regulatory costs (financial requirement).
8. Application of the factor calculated in the previous step to the MCP vectors.
9. Obtaining the network tariff vectors.

For the losses cost flow steps 1 and 4 are applied and redistributed hourly by the LR of customers. The energy function uses a linear distribution. We implement the calculation model in *Matlab 2018B* software. Figure 6 presents the flowchart.

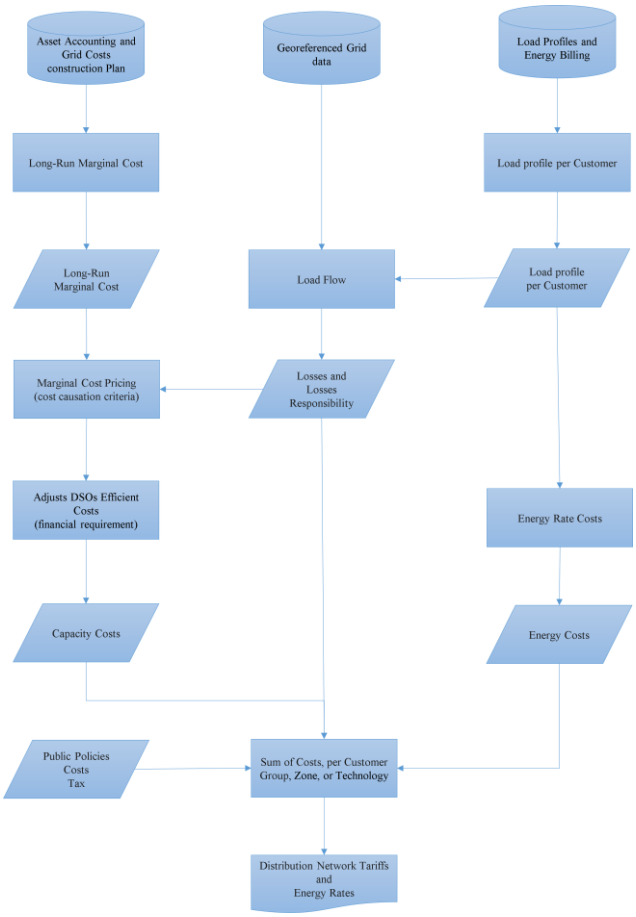

Fig. 6. Locational and Dynamic Distribution System Tariff Process.

Table 2 details the DNT and Energy Rates (ER) calculation processes, according to the Flowchart of Figure 7.

Table 2. Tariff Process.

Process	Description	Inputs	Outputs
Long-Run Marginal Costs	The average accounting costs of transformer and substation by installed capacity ($/kW) and of low voltage and medium voltage grids by type and length ($/kW-km).	Distribution Assets Account and Grid Costs Construction Plan ($), and Assets operating characteristics (kW).	Estimated LRMC ($/kW).
Load Profile per Customer	Energy (kWh) per customer and standard load profile.	Standard load profile and customer energy measurement. The measurement is performed manually for LV and remotely for MV and HV.	Aggregated data for Energy (kWh). Three load profiles for the customer, representing Weekdays, Saturdays, and Sundays.
Load Flow	Distribution load flow using OpenDSS software to define harmonic load components.	Injection measurement data, representation of the grid elements using a georeferencing system, and standard load profiles for weekday, Saturday, and Sunday.	Power losses of the distribution grid and Losses Responsibility (see item 3.1.1)
Losses and Losses' Responsibility	According to item 3.	Customer Load Profile and Netload profile in a frequency domain	$LR_{j,k}$ as defined in Eq. (3) and Losses Costs
Marginal Cost Pricing	According to item 3.	LRMC and Losses Responsibility	$MCP_{k,j,h}$ as defined in Eq. (11)
Adjusts	Adjust to efficient costs: transmission costs, operational costs, network depreciation, remuneration of investments.	Efficient costs and Marginal Cost Pricing	Capacity Costs
Energy Rate Costs	Energy Rates due to operation costs	The mix of the price of Energy Contracts and energy per customer group	Energy Rate Costs ($/kWh)
Sum of Costs	Considered costs associated with distribution transport.	Capacity, losses, energy, and public policy costs.	Tariffs and Energy Rates

Note: LV is Low Voltage; MV is Medium Voltage; and HV is High Voltage.

The process observes the regulatory costs. Secondly, the costs are segregated by consumer classes, resulting in regulated prices in $/kWh. The proposed model can present detailed costs. It is possible to aggregate marginal costs most conveniently by region, consumer class, and technology. Therefore, the statistical evaluation and aggregation of results using weighted average Marginal Cost Pricing.

3.2. Dynamic and Locational DNT Results

The distribution network has 7 HV-MV (138-13.8 kV) transformers, 11.731 HV-LV (13.8-0.22 kV) transformers, and 46 feeders. In addition, there are 171,670 LV customers and 492 MV customers. LV customers have historic average consumption rates of 2,689 kWh per annum and MV customers have historic average consumption rates of 475,880 kWh per year. In LV, households represent 56,4% of total energy and commercial establishments represent 21,6% of total energy. Data from the 2015 year. Geo-referenced single line diagram of the network (MV and LV) is presented in Fig. 7.

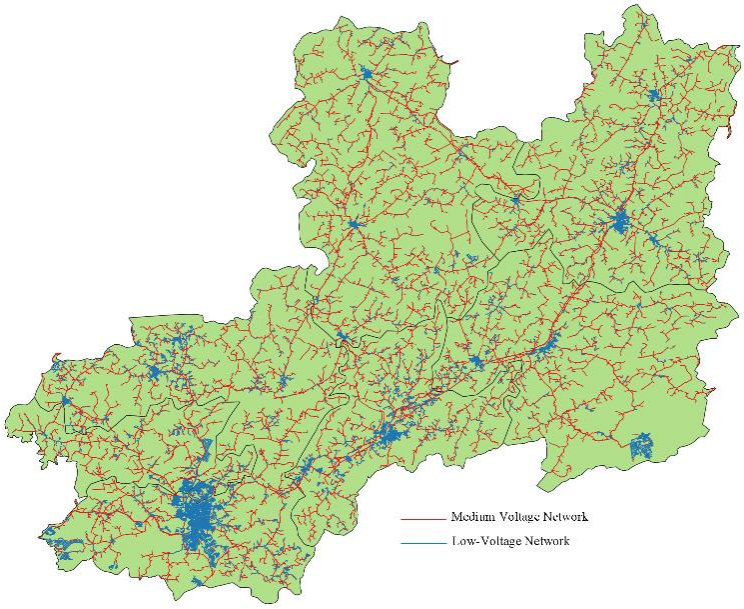

Fig. 7. Low and Medium Voltage Network

For the simulations, revenue data calculated in the Tariff Review process of regulatory bodies, according to data from (ANEEL 2016). Firstly, we aggregate evaluation of tariffs. Secondly, we analyze the tariffs per customer and hourly. Figure 8 presents the average network tariff (including energy rates) in a location function.

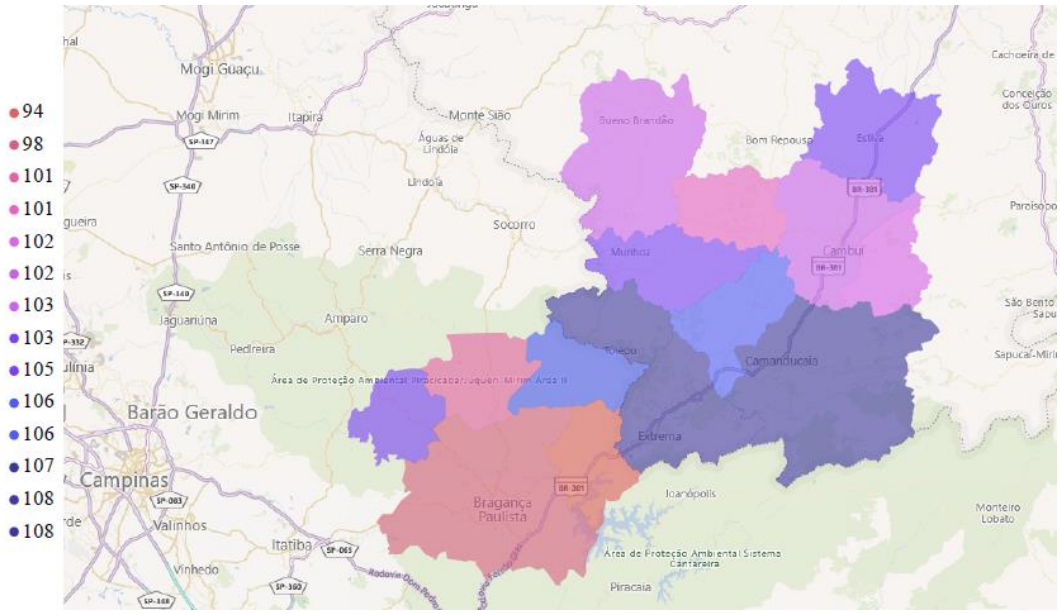

Fig. 8. Low Voltage Tariffs ($/MWh)

Figure 9 presents the statistical day network tariff (including energy rates) in a boxplot time function.

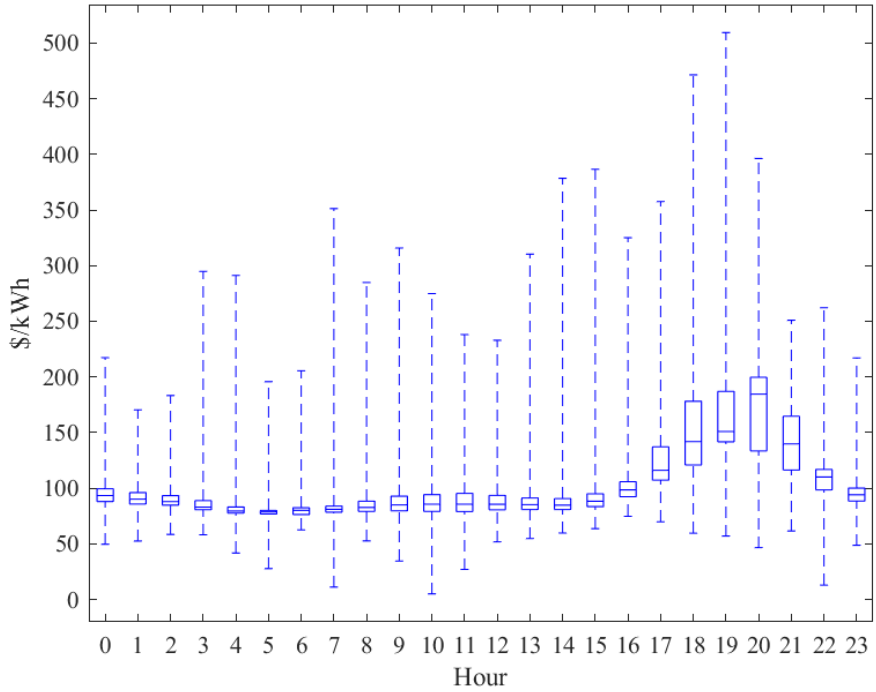

Fig. 9. Boxplot of tariffs for consumers served at low voltage

The runtime was 43 minutes for the test case, considering a computer with an AMD Ryzen 5, 3500U processor, and 12Gb RAM. Finally, different from existing literature, we will adopt the criteria: long-term marginal cost; peak load pricing criteria; large scale

(realistic application); cost causality criteria; and financial requirement. Such criteria are used by regulatory entities and DSOs in a practice tariff design.

4. LOCATIONAL AND DYNAMIC DISTRIBUTION SYSTEM TARIFF APPLIED TO DER

The goal of the following sections is to use the model proposed in 3 to define consumer classes and tariffs, according to cost causality criteria and financial requirements. The main characteristic of DER is its technical and economic impact on the distribution network. Therefore, it demands more sophisticated models aimed at reducing the problem granularity and detailing its cost impacts.

4.1. Price Signal to DER

There is a unification of practices in electrical pricing due to the organizational form or routine of DSO and regulatory bodies (Yakubovich, Granovetter, and Mcguire 2005). In Ref. (Freitas Gomes, Perez, and Suomalainen 2021) authors describe how tariff structures affect crucial elements to be considered before investing in DERs and how they can affect cost recovery from the DSOs. In addition, tariff structures can influence DERs adoption patterns and the utility death spiral (Moncada et al. 2021a). To achieve an optimal tariff, regulatory entities need to set it as close as possible to the true LRMC for the system, to drive customers to make socially best DER adoption decisions (Carvallo et al. 2020).

The initial discussion of tariff structure should be how to classify its consumers, for the purposes of cost-reflective, measurement, and billing. The consumer classes must have uniformity in price elasticity of consumption and economic conditions (DORAU 1930). Hence, nowadays, sophisticated retailers or DSOs dissect residentials into six or more sub-segments. Marketing channels are specifically constructed to target customers in these discrete sub-segments. In addition, some households have Rooftop-PV or use automated systems. Therefore, with the number of consumer sub-divisions increasing and the mix of discrete household metered loads emerging, the number of products necessarily multiplies (Simshauser 2018). For better efficient energy management of customers, it is also essential for DSOs to offer pricing to different groups of customers and dynamic pricing (Tsao et al. 2022).

In Ref. (Burns and Mountain 2021), the authors estimate the elasticity of substitution for households on Time-Of-Use (TOU) tariffs using a sample of 6957 electricity bills in Australia. Your findings suggest that Australian households respond weakly to time-varying tariffs, and customers in the lowest socio-economic areas do not respond at all. According to (Cosmo and O'Hora 2017), TOU and financial feedback influenced the degree to which consumers reduced usage. The data suggest that households reduced consumption rather than shifting consumption from the peak. The lack of appropriate technologies possibly made it difficult for consumers to switch consumption habits. In Ref. (George and Bell 2018), the authors use a pay-to-play recruitment approach for more than 50,000 customers. The pilots also showed that TOU rates can produce a small reduction in overall energy use. The authors in Ref. (Gyamfi, Krumdieck, and Urmee 2013) investigate the challenges in achieving effective voluntary demand reduction based on literature. The results indicate that a high fraction of households does not respond to price.

On the other hand, dynamic pricing is in the class of price response programs that have gained the greatest attention in recent times (Gyamfi, Krumdieck, and Urmee 2013). Authors in Ref. (Geng et al. 2019) present a smart charging management system considering the elastic response of electric vehicle users to price. They conclude that EVRs can respond to the different electricity prices, and the coordinated pricing results are effective to guide the charging behavior of EVRs. In addition, EVR will change load characteristics, such as high demand price elasticity, charging schedule options without discomfort, and control of charging time (slow, semi-fast, fast, and ultra-fast). The flat tariff design does not provide incentives for EVR load modulation (Küfeoğlu, Melchiorre, and Kotilainen 2019).

Therefore, this study explores two different tariff design approaches. First, we will evaluate a flat rate under cost causality criteria in a low voltage customer that tends not to respond to hourly price signals, applied to Rooftop-PV. Second, we will evaluate time-varying pricing applied to BESS and EVR, with high demand price elasticity.

4.2. Rooftop-PV

Net-metering can over-incentivize Rooftop-PV acceptance and force consumers without Rooftop-PV to pay the residual costs that prosumers manage to offset. In turn, the increase

in the DSO costs may incentivize customers without Rooftop-PV to adopt the resource, creating a positive feedback loop (Schittekatte, Momber, and Meeus 2018; Moncada et al. 2021a). The aggregation of Rooftop-PV to the residential consumer will not change its low intraday elasticity. Therefore, we define a flat tariff ($/kWh) that is consistent with cost causality criteria, Pareto optimal, and financial requirements. According to (Viscusi, Harrington Jr, and Sappington 2018), in a Pareto optimal *"the equilibrium cannot be replaced by another one that would increase the welfare of some consumers without harming others […] One tool for evaluating the effect of a policy change is the Pareto criterion"*.

For the simulations, we adopt the curve represented in Figure 10 as the model for Rooftop-PV insertion. Furthermore, the load profiles aggregated by consumer class are presented.

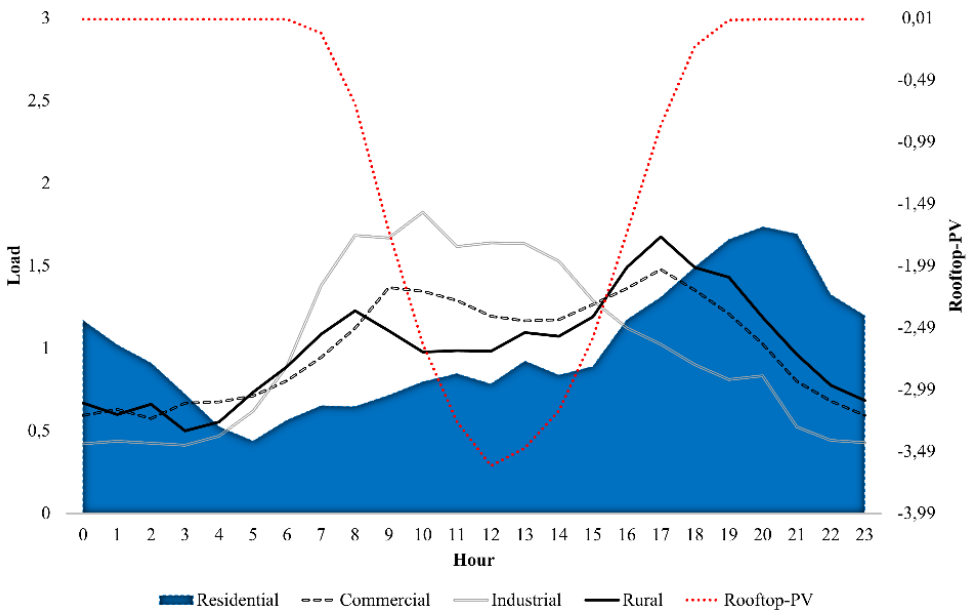

Fig. 10. Rooftop-PV and Load profile.

In practice, the growth of Rooftop-PV tends to be lower than the distribution load growth. Thus, the simulations aim to evaluate the effect of the additional costs in the network due to the Rooftop-PV adoption.

With the base-case scenario proposed in section 3, the Rooftop-PV is inserted randomly in 1% of customers. The customer is selected and associated with the generation curve corresponding to 80% of the energy consumption. The load growth counterpart of the complementary customers (without Rooftop-PV) is considered. Thus, the simulations

have the same total distributed energy, disregarding the effect of load growth/reduction on tariffs, according to a long-term cost analysis.

The adjustment factor to revenues of step 7 (item 3.1.4) is held steady according to the base case. Therefore, our analyses reveal that the necessary revenue increases to maintain the financial requirement of the DSO (case Rooftop-PV). The Rooftop-PV adoption results in a decrease in the load factor of the distribution network, i.e., it implies an increase in long-term marginal costs. We adopted the energy injected into the network as a base for the tariff. Taking the necessary additional revenue due to Rooftop-PV (case Rooftop-PV minus case-base), and dividing by the injected energy of prosumers, we have the average tariffs for consumer class, as shown in Table 3.

Table 3. Results.

Consumer Class	DNT ($/MWh)	Low-Voltage Tariff Ratio
Residential	52.66	80.51%
Commercial/Industry	38.88	59.44%
Rural	33.22	50.79%

Table 3 also provides the relation between the tariffs calculated for the Rooftop-PV insertion scenario and the base-case scenario of 108.75 $/MWh, referring to DNT. The practical use is applying the factors obtained for DNT in a general way for all customers with Rooftop-PV, segregating by customer classes.

4.3. Battery Energy Storage Systems

Several studies are using the behind-the-meter approach in the economic analysis of BESS. In (Sharma, Han, and Sharma 2019) the authors implement a residential storage system optimization algorithm, concluding that BESS sizing depends on the tariff structures. In (Barcellona et al. 2018), the authors conclude that it is currently not economically feasible to install BESS in network-connected customers. The economic feasibility of peak shaving using BESS in residential customers for short peak injection is given in (Koskela et al. 2019; Biroon, Biron, and Hadidi 2020). Nevertheless, in these papers, network tariff is an independent or exogenous variable.

The time-varying pricing can be another driver for the acceptance of behind-the-meter BESS and influence the dispatch of these assets. These tariffs are considered in many storage scheduling and sizing methods as well as in prosumer and microgrid DER models (Heleno et al. 2020b). Thus, we define for residential consumers in the system presented

in Figure 8 a time-varying pricing (see also Figure 9). The goal is to quantify the economic impact of applying small residential energy storage units in the network.

The Economic Benefit (EB) for peak shaving is composed of the load in the off-peak (*OP*) and the discharge in the peak (*P*) for the application of the two-part tariff. Considering the efficiency of the loading regime ε_{in} and unloading ε_{out}, we have that EB will be given by the ratio between DNT in the tariff stations and Energy Rates (ER), according to Eq. (12).

$$EB = DNT_P - \frac{DNT_{OP}}{\varepsilon_{in} \cdot \varepsilon_{out}} - ER \cdot \ (1 - \varepsilon_{in} \cdot \varepsilon_{out}) \quad (12)$$

We considered $\varepsilon_{in} = \varepsilon_{in} = 90\%$. By assuming a fixed recharge time of 8 consecutive hours in the lowest tariff period for the location and a discharge time ranging from 2 hours to 5 hours, the probability distributions in Figure 11 are obtained, according to Eq. (12).

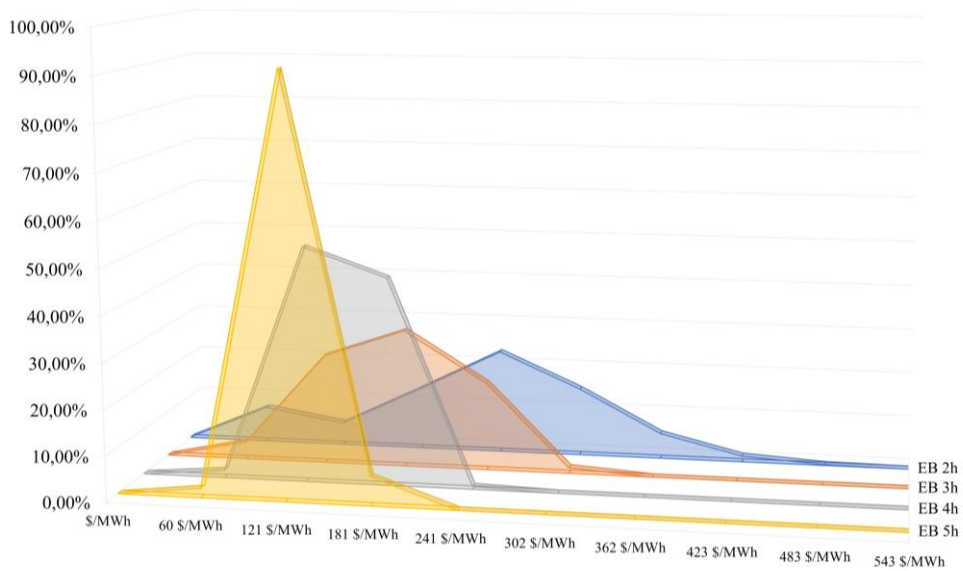

Figure 11. EB Probability distributions.

The shorter the discharge time the higher the EB. Furthermore, there is a large variation of EB as a function of the connection point. Table 4 presents some notable points of Figure 11.

Table 4. EB results.

Type	EB 2h	EB 3h	EB 4h	EB 5h
EB by Average Tariff	132.19	114.88	104.41	90.92
Average EB	213.46	160.57	128.38	106.02
EB decile upper	333.51	223.54	166.44	128.47

The EB by average tariff results from the application of a TOU tariff. The average tariff curve's variance will be greater than the variance of the weighted average tariff curve, and thus the application of a single tariff for the entire DSO area tends to reduce the feasibility of the BESS adoption. However, with the application of locational tariffs by identifying the 10% of customers with the highest EB and a 2-hour discharge period, it is possible to obtain an EB of $ 333.51 per kWh injected into the distribution network.

4.4. Electric Vehicle Recharging

Dynamic pricing is in the class of price response programs that has garnered the greatest attention in current times. There are three approaches for the EVR economic evaluation costs in the distribution network. The first is the one that considers the SRMC. Paper (Ghosh and Aggarwal 2017) proposes a pricing mechanism for EVR depending on energy volume, recharge time, and type (renewable or conventional). The model demonstrates that it is possible to reduce the peak netload with an economic signal. Paper (Wang et al. 2018) presents an SRMC model with dynamic energy pricing, with the profit maximization objective of the recharging station. The second approach uses LRMC (Chekired, Khoukhi, and Mouftah 2018). The third applies in EVR stations that use the DLPM model to obtain the SRMC (Zheng et al. 2019). However, this research does not cover the completeness of DSO networks.

Likewise, electricity tariffs could be designed to achieve operation objectives that are a proxy for potentially more effective decisions made by a centralized operator. The long-term planning processes could be improved by integrating bulk power and DSO planning (Carvallo et al. 2020). Therefore, a long-term approach is necessary.

We evaluate the impact of EVR in a network system presented in Figure 8 using the Nissan Leaf vehicle domestic recharge of 3.25 kW, 0.188 kWh/km, recharge efficiency of 92%, and an average trip in Brazil of 13.3 km (NTU 2017). The EVRs are applied to Residential customers. We adopted a minimum recharge time of 0.8363 hours. We also considered a recharge in up to 8 hours as the upper limit of the time of complete domestic recharge using Wallbox (home charger). Finally, the recharge time utilizes a truncated normal distribution.

When considering Uncontrolled Charging, in which all customers perform charging in the average period of 18 hours, and truncated normal distribution condition, we obtain the average and top decile tariffs, presented in Figure 12 and Figure 13.

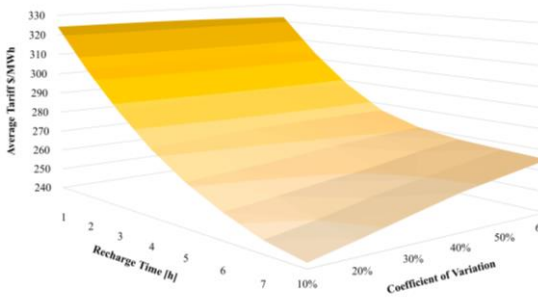

Fig. 12. Average Tariff Uncontrolled Charging.

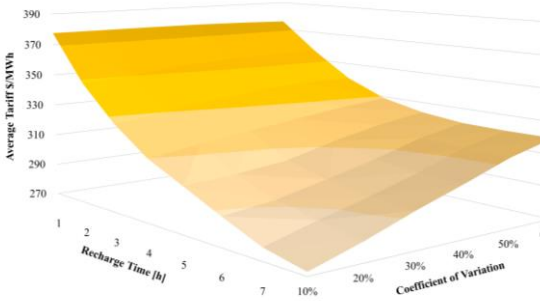

Fig. 13. Decile upper Uncontrolled Charging.

The axis Recharge Time represents a value between 0.8363-8 hours, and Coefficient of Variation a statistic of truncated normal distribution.

In turn, when considering Smart Charging, in which all customers recharge in the period that individually minimizes their costs, we obtain Figure 14, which represents the average cost per MWh, as a function of recharging time and coefficient of variation of the truncated normal distribution. Furthermore, from Figure 15, it is possible to observe the cost curve for the lower decile.

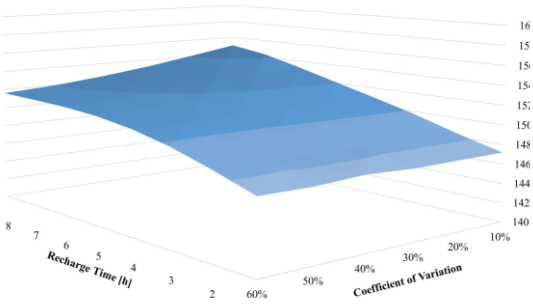

Fig. 14. Average Tariff Smart Charging.

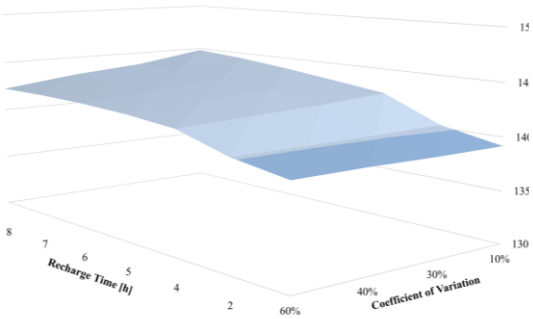

Fig. 15. Lower Decile Smart Charging.

Our analyses reveal an average tariff of 154.98 $/MWh for Smart Charging for charging time of 8 hours, against one of up to 265.77 $/MWh for Uncontrolled Charging. However, evaluating the upper decile for Uncontrolled Charging of 320.27 $/MWh and the lower

decile for Smart Charging of 144.81 $/MWh it is possible to observe the dimension of the efficiency loss due to the lack of network time-varying pricing for EVR.

5. CONCLUSIONS AND RECOMMENDATIONS

Consumers are traditionally divided into limited customer groups, due to homogeneous elasticity characteristics and consumption habits. The consumer classes met the requirements of the tariff structure of the distribution electricity systems. However, the characteristic of investment capacity in Distributed Energy Resources must be considered in the evolution of the current tariff structure. There are no off-the-shelf models for the tariff structure, i.e., they must be evaluated on a case-by-case basis, according to the technical, economic, and social characteristics of the area.

However, cost causation criteria, financial requirement, and tariff stability must be considered when setting the tariffs for the new kind of standard customers. Thus, more accurate tariff structure models should be used to evaluate the economic impacts due to the variability of the characteristics of consumers, besides changing their consumption behavior through automation and electric vehicle recharging, and investment in energy storage and production.

The findings presented in this paper emphasize the importance of DER tariff structure to make explicit the marginal and average costs per customer. The model substantially increases the calculation precision of impact costs and tariff, which enables statistical analysis of regionalized data and by customer characteristics, i.e., leaving it up to regulatory entities to define tariff structure.

The Pareto optimal tariff is applied for Rooftop-PV. Our results indicate that it varies due to the load profile, and it is advisable to employ at least one differentiated tariff by consumer class. The findings presented in this paper emphasize the importance of a tariff structure that includes periods of optimal distribution network cost for BESS in peak shaving. However, for the correct signaling, it is necessary to reduce the temporal and locational granularity. The findings presented in this paper emphasize the importance of locational and dynamic price, indicating the best benefits of installing BESS for peak shaving and sharing efficiency gains.

The findings presented from BESS can be applied to EVR. Furthermore, there is a high price response because there will be no disconformity in changing the load profile. Thus, there will be a substantial increase in the consumption price elasticity, reducing the market response.

The tariff structure chosen is essential for a fair and efficient distribution system with vast DER adoption. The proposed model can offer more cost causality criteria designs by reducing temporal and locational granularity, which would allow studying the impact of the DER in tariff structure.

ACKNOWLEDGMENTS

This work was partially financed by Coordination for the Improvement of Higher Education Personnel - Brazil (CAPES- Coordenação de Aperfeiçoamento de Pessoal de Nível Superior).

REFERENCES

Alvarez, David L., Sergio R. Rivera, and Enrique E. Mombello. 2019. "Transformer Thermal Capacity Estimation and Prediction Using Dynamic Rating Monitoring." *IEEE Transactions on Power Delivery* 34 (4): 1695–1705. https://doi.org/10.1109/TPWRD.2019.2918243.

Anaya, Karim L., and Michael G. Pollitt. 2015. "Integrating Distributed Generation: Regulation and Trends in Three Leading Countries." *Energy Policy* 85 (October): 475–86. https://doi.org/10.1016/j.enpol.2015.04.017.

ANEEL. 2016. "Technical Report on Load Characterization for Survey of Typical Curves of the 4th Tariff Review Cycle. Process N° 48581.001273/2016-00." Brasilia.

Ansarin, Mohammad, Yashar Ghiassi-Farrokhfal, Wolfgang Ketter, and John Collins. 2020. "The Economic Consequences of Electricity Tariff Design in a Renewable Energy Era." *Applied Energy* 275: 115317. https://doi.org/https://doi.org/10.1016/j.apenergy.2020.115317.

Barcellona, Simone, Luigi Piegari, Vincenzo Musolino, and Christophe Ballif. 2018. "Economic Viability for Residential Battery Storage Systems in Grid-Connected PV Plants." In *IET Renewable Power Generation*, 12:135–42. Institution of Engineering and Technology. https://doi.org/10.1049/iet-rpg.2017.0243.

Biggar, Darryl. 2010. "Fairness in Public-Utility Regulation: A Theory." *Agenda: A Journal of Policy Analysis and Reform* 17 (1): 5–29.

Biroon, Roghieh Abdollahi, Zoleikha Abdollahi Biron, and Ramtin Hadidi. 2020. "Commercial Load Profile Sensitivity Analysis to Electricity Tariffs and Battery Characteristics." *IEEE Transactions on Industry Applications* 56 (2): 1021–30. https://doi.org/10.1109/TIA.2019.2959000.

Blackhall, Lachlan, Gabrielle Kuiper, Larissa Nicholls, and Paul Scott. 2020. "Optimising the Value of Distributed Energy Resources." *Electricity Journal* 33 (9). https://doi.org/10.1016/j.tej.2020.106838.

Brandstätt, Christine, Gert Brunekreeft, and Nele Friedrichsen. 2011. "Locational Signals to Reduce Network Investments in Smart Distribution Grids: What Works and What Not?" *Utilities Policy* 19 (4): 244–54. https://doi.org/10.1016/j.jup.2011.07.001.

Brown, Toby, Ahmad Faruqui, and Léa Grausz. 2015. "Efficient Tariff Structures for Distribution Network Services." *Economic Analysis and Policy* 48 (July): 139–49. https://doi.org/10.1016/j.eap.2015.11.010.

Burger, Scott P, Christopher R Knittel, Ignacio J Pérez-Arriaga, Ian Schneider, and Frederik vom Scheidt. 2020. "The Efficiency and Distributional Effects of Alternative Residential Electricity Rate Designs." *The Energy Journal* 41 (1).

Burger, Scott, Ian Schneider, Audun Botterud, and Ignacio Pérez-Arriaga. 2019. "Fair, Equitable, and Efficient Tariffs in the Presence of Distributed Energy Resources." In *Consumer, Prosumer, Prosumager: How Service Innovations Will Disrupt the Utility Business Model*, 155–88. Elsevier. https://doi.org/10.1016/B978-0-12-816835-6.00008-5.

Burns, Kelly, and Bruce Mountain. 2021. "Do Households Respond to Time-Of-Use Tariffs? Evidence from Australia." *Energy Economics* 95 (March). https://doi.org/10.1016/j.eneco.2020.105070.

Bustos, Cristian, David Watts, and Daniel Olivares. 2019. "The Evolution over Time of Distributed Energy Resource's Penetration: A Robust Framework to Assess the Future Impact of Prosumage under Different Tariff Designs." *Applied Energy* 256 (December): 113903. https://doi.org/10.1016/j.apenergy.2019.113903.

Carvallo, Juan Pablo, Nan Zhang, Sean P. Murphy, Benjamin D. Leibowicz, and Peter H. Larsen. 2020. "The Economic Value of a Centralized Approach to Distributed Resource Investment and Operation." *Applied Energy* 269 (July). https://doi.org/10.1016/j.apenergy.2020.115071.

Caywood, Russell E. 1972. "Electric Utility Rate Economics."

Chekired, Djabir Abdeldjalil, Lyes Khoukhi, and Hussein T. Mouftah. 2018. "Decentralized Cloud-SDN Architecture in Smart Grid: A Dynamic Pricing Model." *IEEE Transactions on Industrial Informatics* 14 (3): 1220–31. https://doi.org/10.1109/TII.2017.2742147.

COHEN, Richard. 2017. "In Golden State, An Uncertain Future For Incumbent 'Utilities.'" *The Electricity Journal* 30 (8): 66–67. https://doi.org/10.1016/j.tej.2017.09.010.

Cosmo, Valeria di, and Denis O'Hora. 2017. "Nudging Electricity Consumption Using TOU Pricing and Feedback: Evidence from Irish Households." *Journal of Economic Psychology* 61 (August): 1–14. https://doi.org/10.1016/j.joep.2017.03.005.

DORAU, Herbert Benjamin. 1930. *Materials for the Study of Public Utility Economics*. 1st ed. New York: The Macmillan Company.

Freitas Gomes, Icaro Silvestre, Yannick Perez, and Emilia Suomalainen. 2021. "Rate Design with Distributed Energy Resources and Electric Vehicles: A Californian Case Study." *Energy Economics* 102 (October). https://doi.org/10.1016/j.eneco.2021.105501.

Fridgen, Gilbert, Micha Kahlen, Wolfgang Ketter, Alexander Rieger, and Markus Thimmel. 2018. "One Rate Does Not Fit All: An Empirical Analysis of Electricity Tariffs for Residential Microgrids." *Applied Energy* 210 (January): 800–814. https://doi.org/10.1016/j.apenergy.2017.08.138.

Garfield, Paul J, and Wallace Francis Lovejoy. 1964. "Public Utility Economics."

Geng, Lijun, Zhigang Lu, Liangce He, Jiangfeng Zhang, Xueping Li, and Xiaoqiang Guo. 2019. “Smart Charging Management System for Electric Vehicles in Coupled Transportation and Power Distribution Systems.” *Energy* 189 (December). https://doi.org/10.1016/j.energy.2019.116275.

George, Stephen S., and Eric Bell. 2018. “Key Findings from California’s Recent Statewide TOU Pricing Pilots.” *Electricity Journal* 31 (8): 52–56. https://doi.org/10.1016/j.tej.2018.09.013.

Ghosh, Arnob, and Vaneet Aggarwal. 2017. “Control of Charging of Electric Vehicles through Menu-Based Pricing under Uncertainty.” In *IEEE International Conference on Communications*. Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/ICC.2017.7997119.

Gyamfi, Samuel, Susan Krumdieck, and Tania Urmee. 2013. “Residential Peak Electricity Demand Response - Highlights of Some Behavioural Issues.” *Renewable and Sustainable Energy Reviews*. Elsevier Ltd. https://doi.org/10.1016/j.rser.2013.04.006.

Hage, Fabio S. el, and Carlos Rufín. 2016. “Context Analysis for a New Regulatory Model for Electric Utilities in Brazil.” *Energy Policy* 97 (October): 145–54. https://doi.org/10.1016/j.enpol.2016.07.014.

Hayat, Muhammad Adnan, Farhad Shahnia, and G. M. Shafiullah. 2019. “Replacing Flat Rate Feed-In Tariffs for Rooftop Photovoltaic Systems with a Dynamic One to Consider Technical, Environmental, Social, and Geographical Factors.” *IEEE Transactions on Industrial Informatics* 15 (7): 3831–44. https://doi.org/10.1109/TII.2018.2887281.

Heleno, Miguel, David Sehloff, Antonio Coelho, and Alan Valenzuela. 2020a. “Probabilistic Impact of Electricity Tariffs on Distribution Grids Considering Adoption of Solar and Storage Technologies.” *Applied Energy* 279 (December): 115826. https://doi.org/10.1016/j.apenergy.2020.115826.

———. 2020b. “Probabilistic Impact of Electricity Tariffs on Distribution Grids Considering Adoption of Solar and Storage Technologies.” *Applied Energy* 279 (December). https://doi.org/10.1016/j.apenergy.2020.115826.

Initiative, M I T Energy. 2016. “Utility of the Future.” *An MIT Energy Initiative Response to an Industry in Transition*.

Koskela, Juha, Kimmo Lummi, Antti Mutanen, Antti Rautiainen, and Pertti Jarventausta. 2019. “Utilization of Electrical Energy Storage with Power-Based Distribution Tariffs in Households.” *IEEE Transactions on Power Systems* 34 (3): 1693–1702. https://doi.org/10.1109/TPWRS.2018.2879612.

Kraning, Matt, Eric Chu, Javad Lavaei, and Stephen Boyd. 2013. “Dynamic Network Energy Management via Proximal Message Passing.” *Foundations and Trends® in Optimization* 1 (2): 73–126.

Küfeoğlu, S., D.A. Melchiorre, and K. Kotilainen. 2019. “Understanding Tariff Designs and Consumer Behaviour to Employ Electric Vehicles for Secondary Purposes in

the United Kingdom." *The Electricity Journal* 32 (6): 1–6. https://doi.org/10.1016/j.tej.2019.05.011.

Lazar, J, C Linvill, M Dupuy, J Shipley, and D Brutkoski. 2017. "Smart Non-Residential Rate Design–Optimizing Rates for Equity." *Integration, and DER Deployment. December*.

Lee, L., and A. A. Girgis. 1988. "APPLICATION OF DFT AND FFT ALGORITHMS TO SPECTRAL ANALYSIS OF POWER SYSTEM LOAD VARIATION." In *Proceedings of the Annual Southeastern Symposium on System Theory*, 26–29. IEEE. https://doi.org/10.1109/ssst.1988.17009.

Li, Xin, Ronald W. Mazur, Dan R. Allen, and David R. Swatek. 2005. "Specifying Transformer Winter and Summer Peak-Load Limits." *IEEE Transactions on Power Delivery* 20 (1): 185–90. https://doi.org/10.1109/TPWRD.2004.837680.

Moncada, J. A., Z. Tao, P. Valkering, F. Meinke-Hubeny, and E. Delarue. 2021a. "Influence of Distribution Tariff Structures and Peer Effects on the Adoption of Distributed Energy Resources." *Applied Energy* 298 (September). https://doi.org/10.1016/j.apenergy.2021.117086.

Moncada, J.A., Z. Tao, P. Valkering, F. Meinke-Hubeny, and E. Delarue. 2021b. "Influence of Distribution Tariff Structures and Peer Effects on the Adoption of Distributed Energy Resources." *Applied Energy* 298 (September): 117086. https://doi.org/10.1016/j.apenergy.2021.117086.

Munasinghe, M. 1981. "Principles of Modern Electricity Pricing." *Proceedings of the IEEE* 69 (3): 332–48. https://doi.org/10.1109/PROC.1981.11970.

Nash, Luther R. 1933. *Public Utility Rate Structures*. New York: McGraw-Hill.

NTU. 2017. "Pesquisa Mobilidade Da População Urbana 2017." Brasília.

O'Shaughnessy, Eric, and Kristen Ardani. 2020. "Distributed Rate Design: A Review of Early Approaches and Practical Considerations for Value of Solar Tariffs." *The Electricity Journal* 33 (3): 106713. https://doi.org/10.1016/j.tej.2020.106713.

Papavasiliou, Anthony. 2018. "Analysis of Distribution Locational Marginal Prices." *IEEE Transactions on Smart Grid* 9 (5): 4872–82. https://doi.org/10.1109/TSG.2017.2673860.

Parhizi, Sina, and Amin Khodaei. 2016. "Interdependency of Transmission and Distribution Pricing." In *2016 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, 1–5. IEEE. https://doi.org/10.1109/ISGT.2016.7781275.

Queiroz, Leonardo M.O., Marcio A. Roselli, Celso Cavellucci, and Christiano Lyra. 2012. "Energy Losses Estimation in Power Distribution Systems." *IEEE Transactions on Power Systems* 27 (4): 1879–87. https://doi.org/10.1109/TPWRS.2012.2188107.

Rana, Rubi, and Sukumar Mishra. 2019. "Day-Ahead Scheduling of Electric Vehicles for Overloading Management in Active Distribution System via Web-Based

Application." *IEEE Systems Journal* 13 (3): 3422–32. https://doi.org/10.1109/JSYST.2018.2851618.

Roselli, Marcio Andrey. 2020. "Dynamic Locational Model for Distribution System Use Charges." São Paulo: University of São Paulo. https://www.teses.usp.br/teses/disponiveis/3/3143/tde-17122020-093701/pt-br.php.

Roselli, Marcio Andrey, André Luiz Veiga Gimenes, Miguel Edgar Morales Udaeta, Eduardo Crestana Guardia, and Leonardo Mendonça Oliveira de Queiroz. 2022. "Technical Loss Estimation Approach in Power Distribution Systems Using Load Model in Frequency Domain." *Electric Power Systems Research* 209 (August): 107982. https://doi.org/10.1016/j.epsr.2022.107982.

Schittekatte, Tim, Ilan Momber, and Leonardo Meeus. 2018. "Future-Proof Tariff Design: Recovering Sunk Grid Costs in a World Where Consumers Are Pushing Back." *Energy Economics* 70 (February): 484–98. https://doi.org/10.1016/j.eneco.2018.01.028.

Schramm, Gunter. 1985a. "Operationalizing Efficiency Criteria in Energy Pricing Policy." In *Criteria for Energy Pricing Policy*, 89–120. Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-94-011-9810-3_4.

———. 1985b. "Operationalizing Efficiency Criteria in Energy Pricing Policy." In *Criteria for Energy Pricing Policy*, 89–120. Springer.

Sharma, Sangeeta v., Phoumin Han, and Vinod K. Sharma. 2019. "Socio-Economic Determinants of Energy Poverty amongst Indian Households: A Case Study of Mumbai." *Energy Policy* 132 (September): 1184–90. https://doi.org/10.1016/j.enpol.2019.06.068.

Simshauser, Paul. 2016. "Distribution Network Prices and Solar PV: Resolving Rate Instability and Wealth Transfers through Demand Tariffs." *Energy Economics* 54 (February): 108–22. https://doi.org/10.1016/j.eneco.2015.11.011.

———. 2018. "Price Discrimination and the Modes of Failure in Deregulated Retail Electricity Markets." *Energy Economics* 75 (September): 54–70. https://doi.org/10.1016/j.eneco.2018.08.007.

Sioshansi, Fereidoon. 2020. "What Lies Behind-the-Meter and Why It Matters?" In *Behind and Beyond the Meter*, 3–29. Elsevier. https://doi.org/10.1016/B978-0-12-819951-0.00001-3.

Sioshansi, Ramteen. 2016. "Retail Electricity Tariff and Mechanism Design to Incentivize Distributed Renewable Generation." *Energy Policy* 95 (August): 498–508. https://doi.org/10.1016/j.enpol.2015.12.041.

Steiner, Peter O. 1957. "Peak Loads and Efficient Pricing." *The Quarterly Journal of Economics* 71 (4): 585–610.

Tsao, Yu Chung, Tsehaye Dedimas Beyene, Vo van Thanh, Sisay Geremew Gebeyehu, and Tsai Chi Kuo. 2022. "Power Distribution Network Design Considering the

Distributed Generations and Differential and Dynamic Pricing." *Energy* 241 (February). https://doi.org/10.1016/j.energy.2021.122828.

Turvey, Ralph. 2017. *Optimal Pricing and Investment in Electricity Supply*. Routledge. https://doi.org/10.4324/9781315144207.

Viscusi, W Kip, Joseph E Harrington Jr, and David E M Sappington. 2018. *Economics of Regulation and Antitrust*. MIT press.

Wang, Shuoyao, Suzhi Bi, Ying Jun Angela Zhang, and Jianwei Huang. 2018. "Electrical Vehicle Charging Station Profit Maximization: Admission, Pricing, and Online Scheduling." *IEEE Transactions on Sustainable Energy* 9 (4): 1722–31. https://doi.org/10.1109/TSTE.2018.2810274.

Yakubovich, Valery, Mark Granovetter, and Patrick Mcguire. 2005. "Electric Charges: The Social Construction of Rate Systems." *Theory and Society* 34 (5–6): 579–612. https://doi.org/10.1007/s11186-005-4198-y.

Zhang, Kai, Sarmad Hanif, Christoph M. Hackl, and Thomas Hamacher. 2019. "A Framework for Multi-Regional Real-Time Pricing in Distribution Grids." *IEEE Transactions on Smart Grid* 10 (6): 6826–38. https://doi.org/10.1109/TSG.2019.2911996.

Zheng, Yu, Yue Song, David J. Hill, and Ke Meng. 2019. "Online Distributed MPC-Based Optimal Scheduling for EV Charging Stations in Distribution Systems." *IEEE Transactions on Industrial Informatics* 15 (2): 638–49. https://doi.org/10.1109/TII.2018.2812755.