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Full-length article

Evaluating demand response through the time of use model in off-grid regions

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ABSTRACT

Motivated by the goal of increasing the use of renewable energies as a vital part of the energy transition, altering energy consumption in off-grid areas, and involving consumers in the decision-making process of the electricity market, demand response programs are considered essential measures to achieve these goals without requiring highly advanced technologies. The research findings demonstrate that the time-of-use model aids the transition to cleaner energy, offering multiple benefits to consumers.These benefits include reduced energy bills, enhanced quality of life due to lower CO2 emissions, decreased energy subsidies, and reduced dependency on diesel fuel for electricity generation in regions where approximately 84 % of the capacity is derived from diesel. An innovative aspect of this study is proposing the transition from a quasi-inelastic to elastic demand electricity market in off-grid areas in Colombia, based on the evaluated benefits of the Time of Use Model over a specific time horizon. The principal reduction results related to the base consumption in the case study are as follows: peak hours (52.5 kWh/day), hours of maximum solar radiation (203.2 kWh/day), and CO_2 emissions (10 TonEq/year). These findings confirm that demand response is critical in enabling and facilitating the energy transition in off-grid regions, where renewable energy sources and economic incentives are underutilized

1. Introduction

Demand Response involves adjusting electricity usage to align with price signals or economic incentives set by energy providers. This allows consumers to actively manage their energy consumption and significantly reduce and modify energy use within the energy system [1]. One of the challenges of this research is to model the behavior of energy demand in the municipality of Miraflores, a region isolated from the power grid. This involves incorporating Demand Response programs, using TOU and TOU INC mathematical models.. With the results obtained, it is intended to replicate the model in other areas not connected to the regional electricity distribution networks, such as NIZ [2]. These regions are characterized by significant geographic dispersion, diverse renewable energy potential, and limited energy data. The promotion of the DR model is fundamental due to its potential to improve efficiency in the coverage of energy demand, increase the reliability of the energy system, and encourage the adoption of new tariff models based on prices and economic incentives [3,4].

In Colombia, the tariff system for residential users is based on a tariff known as Monomial, which means that it has a single value expressed in $/kWh regardless of the time or amount of consumption; this type of tariff does not indicate to residential users the price of electricity based on their daily demand [5,6]. The subsidy regulations and electricity service tariffs that apply in regions not connected to the grid, as is the case of the municipality of Miraflores, are different from the tariff formulas that apply in the National Interconnected System (NIS). The cost of electricity and the price paid by consumers is known as the tariff structure, which is calculated by adding the costs of each stage of the electricity value chain. The price of electricity is determined based on its average costs and represents a constant value for the user, therefore the price does not influence the decision to consume more or less electricity at any given time. It is essential to examine how the TOU model in this off-grid region encourages the shifting of energy consumption to different times of the day with pre-set electricity prices.

Abbreviations: DR, Demand Response; TOU, Time of Use; TOU+INC, Time Of Use +Incentives; NIZ, Non-Interconnected Zones of Colombia; NIS, National Interconnected System; CPP, Critical Peak Price; RTP, (Real-Time Price; MLPM, Mixed Linear Programming Model; ARIMA, Auto Regressive Integrated Moving Average.

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Regarding the benefits of demand response (DR) models, there are advantages from the demand side. These include reducing energy consumption during high tariff prices and shifting consumption to periods of intermediate demand [3]. This dynamic encourages active consumer participation in the energy market. It is essential to promote DR programs due to their potential to increase energy demand coverage in off-grid regions efficiently, improve the reliability of an energy system, and encourage the adoption of new tariff models based on prices and economic incentives. Related studies incorporate optimization theories to DR programs by reducing electricity costs and increasing demand elasticity [7–10]. Now, from the generation side, Other aspects related to network decongestion and energy optimization are mentioned in [11]. One key benefit is the integration of renewables into the power grid, which is easier with DR programs. While renewables experience fluctuations in their supply due to site-specific weather conditions or peak hours, the flexibility of DR effectively aligns with this variability, meaning that energy consumption can be shifted to periods of higher renewable energy production. Renewables, therefore, influence the setting of optimal electricity prices due to their costs and are promoted through DR at specific times [3,12]. Different conceptual developments and mathematical formulations of DR models are detailed in [13–16].

Through mathematical modeling, this article contributes to the understanding and importance of the dynamics of DR programs in energy behavior, as well as the possible convergence of these dynamics with the implications of reducing energy consumption, CO_2 emissions, and electricity prices. This paper is organized as follows: First, a literature review describing the classification of DR programs, the advantages of their application, and related mathematical models. Second, a mathematical TOU model supplemented with economic incentives is described and formulated. Third, numerical simulations and analysis of results are carried out under different scenarios, such as the incorporation of incentives according to the percentage of demand reduction by the consumer, variation of electricity prices by hourly segments, and self-generation at peak solar radiation hours. Finally, conclusions are drawn about the impacts of DR in the Off-grid regions known as NIZs in Colombia. The results of this study enable the proposal of a new framework for the electricity market in this economically underdeveloped region, enhancing demand elasticity and facilitating the local energy transition

2. Demand response options

Throughout the literature, it has been identified that demand response programs are classified into two groups: price and economic incentives; in the first option, consumers voluntarily change or reduce their consumption in response to economic signals sent by a generating agent, and the following programs are identified among others: TOU, CPP, RTP . For the second option, programs based on economic incentives are identified as voluntary, mandatory, and market programs [3]. The time-of-use model is characterized by setting electricity prices in advance by periods, representing the electricity's levelized cost. In different articles, it is observed that the periods are classified into valley hours, where energy demand and energy prices are relatively low; peak hours, where energy demand and prices are high; and finally, off-peak hours, where demand and prices acquire intermediate values [17–19]. Authors typically express the TOU model as a linear equation, where each hour's adjusted energy demand is determined based on the price-demand elasticity of price variation and electricity demand over periods [20,21]. While not an essential part of the present research, other models found in the literature are the RTP (Real-Time Price) model, which establishes prices that fluctuate continuously during a day, as opposed to Time of Use Tariffs, which establish electricity prices by hourly segments [22]. Providing a variable price signal with a given time-frequency can contribute to several system benefits, including decongestion of distribution networks, reduction of technical losses, and postponement of investments in generation capacity [23]. Finally, the CPP (Critical Peak Price) model, although not developed in this article, combines the previous models; it differs in that it increases the price of energy during peak hours mainly due to programmed or critical situations to discourage consumption during this period, in some cases, incentives are implemented by lowering the price of energy during off-peak hours [24,22]

Referring to mathematical models applied to DR, in [25], a linear optimal TOU model is formulated that makes energy demand more flexible in the face of power variations in electrical distribution networks. Also, in reference [26], a mixed linear programming model (MLPM) is identified, which integrates TOU models with other DR models applied it to a residential community with the availability of renewable energy potentials and energy storage.

Existing demand response models and studies have mostly been developed for grid-connected regions [19]. This study addresses the main research gaps by applying TOU modeling in off-grid areas, highlighting the challenges and opportunities often overlooked in these contexts. It is a pioneering effort to assess the feasibility and effectiveness of the TOU model in off-grid regions characterized by centralized electricity infrastructures and significantly different energy generation and consumption patterns compared to those found in grid-connected areas. It effectively addresses several critical gaps.: a) *Integration with Renewable Energy Resources*: The off-grid regions studied have significant potential for renewable energy sources, such as solar and hydro. However, previous studies on demand response have not sufficiently explored how renewable energy generation impacts demand response strategies in these areas. This research aims to fill that gap by examining how renewable generation periods can be incorporated into TOU pricing models to optimize and modify energy consumption patterns. b) *Elasticity demand*: A significant gap in the existing literature is the lack of research on how the adoption of renewable energy affects demand elasticity in off-grid regions, particularly in the context of TOU pricing models. The relationship between self-generation using renewable energy and time-varying pricing remains poorly understood. Therefore, a key challenge of this study is to assess how sensitive demand is to price fluctuations and to determine the extent to which renewable energy adoption influences or mitigates demand elasticity within TOU pricing models.

From the literature review and other related literature, there is no evidence of the application of the TOU Model to solve problems related to inelastic demand, sizing, and fuel consumption in Off-grid regions of Colombia, nor the results of the application of this model.

3. Formulation model

3.1. Price-Based demand response modeling

Elasticity is an essential concept in economic theory. It quantifies how a variable changes when another variable is modified. It is used in analyzing demand, different types of goods in consumer theory, marginal concepts in the theory of the firm, and the distribution of wealth [27]. The concept of elasticity in energy terms refers to the sensitivity of energy demand to changes in the price of electricity [3]. This is typically expressed as $E = \rho o.\partial o/do.\partial\rho$. Accordingly, the elasticity of demand in the i-th period due to price changes in the j-th period can be mathematically defined as follows: $E(i,j) = \rho o(j).\partial d(i)/do(i).\partial\rho(j)$, and is referred to as cross elasticity. Furthermore, the elasticity of demand to price changes in the same period is known as self-elasticity.

When considering energy consumption that cannot be shifted from one period to another, such as with lighting systems used at specific times, we model these consumptions under the concept of "Autoelasticity." For consumptions that can be shifted, such as those managed at times other than the usual periods of use, we model them under the concept of Cross Elasticity. To model a 24-hour energy consumption period, a 24×24 matrix must be constructed. In this matrix, the diagonal elements represent the Autoelasticities, and the non-diagonal elements represent the Cross Elasticities [17,3], as shown in Eq. (1).

$$\begin{bmatrix} \Delta d(1) \\ \Delta d(2) \\ \dots \\ \dots \\ \dots \\ \Delta d(24) \end{bmatrix} = \begin{bmatrix} E(1,1)\ E(1,3)\ \dots\ E(1,24) \\ E(2,1)\ E(i,j)\ \dots\ \dots \\ \dots\ \dots\ \dots \\ \\ E(24,j) \end{bmatrix} \text{X} \begin{bmatrix} \Delta\rho(1) \\ \Delta\rho(j) \\ \dots \\ \dots \\ \Delta\rho(24) \end{bmatrix} \tag{1}$$

Column j of this matrix indicates how a change in price during period j affects demand during all periods. Where Δd(i) is the change in demand from an initial period to a final period, Δp(i) represents the change in electricity prices from an initial period to a final period.

- ***TOU Model***

According to Eq. (2), the TOU model is formulated as a linear equation where the hourly modified energy demand is determined as a function of the price-demand elasticity, the electricity price variation, and the electricity demand variation in period intervals [20].

$$\mathrm{d}(i) = do(i) + \sum_{j=1}^{24} \left(Eo(i,j) \frac{do(i)}{po(j)} . [p(j) - po(j)] \right) \tag{2}$$

d(i)= demand in the period i with application DR
do(i)= Initial Demand in period i
Eo(i,j)= Elasticity of Demand as a function of price
po(j)= Initial price of electricity before DR ($/kWh)
p(j)= Final price of electricity with DR application ($/kWh)

3.2. Price-Based demand response and incentives

- ***TOU Model+INC***

The TOU+INC model effectively integrates pre-established energy prices with economic incentives to reward consumers for load reduction in specific periods. Eq. (3) simplifies a multiperiod extended linear model, contributing to a more streamlined and efficient process. A (j) symbolizes the economic incentive a demand aggregator provides to a consumer, encouraging them to reduce energy consumption in a specific period. This model is designed to determine the advantages consumers can enjoy by adjusting their consumption habits.

$$\mathrm{d}(i) = \left\{ do(i) + \sum_{j=1}^{24} \left(Eo(i,j) \frac{do(i)}{po(j)} . [p(j) - po(j) + A(j)] \right) \right\} * \{1 + E(i)[p(i) - po(i) + A(i)]/po(i)\} \tag{3}$$

Where:

E(i)= Elasticity of Demand in period i
po(i)= Initial price of electricity before DR (USD/kWh)
p(i)= Final price of electricity with DR application (USD/kWh)
A(i)= Economic incentive in period i ((USD/kWh)

The behavior of electric loads that respond to economic incentives is considered a function of this recognition. The S-shaped curve used in [21] and shown in Fig. 1 is proposed to model this dependence.

This curve represents a graphical function where the incentive, as an independent variable granted to the consumer, promotes the percentage of participation in the reduction of energy consumption at peak hours or in a given period. The maximum percentage of participation, $\beta dmax$, can be determined from Eq. (4).

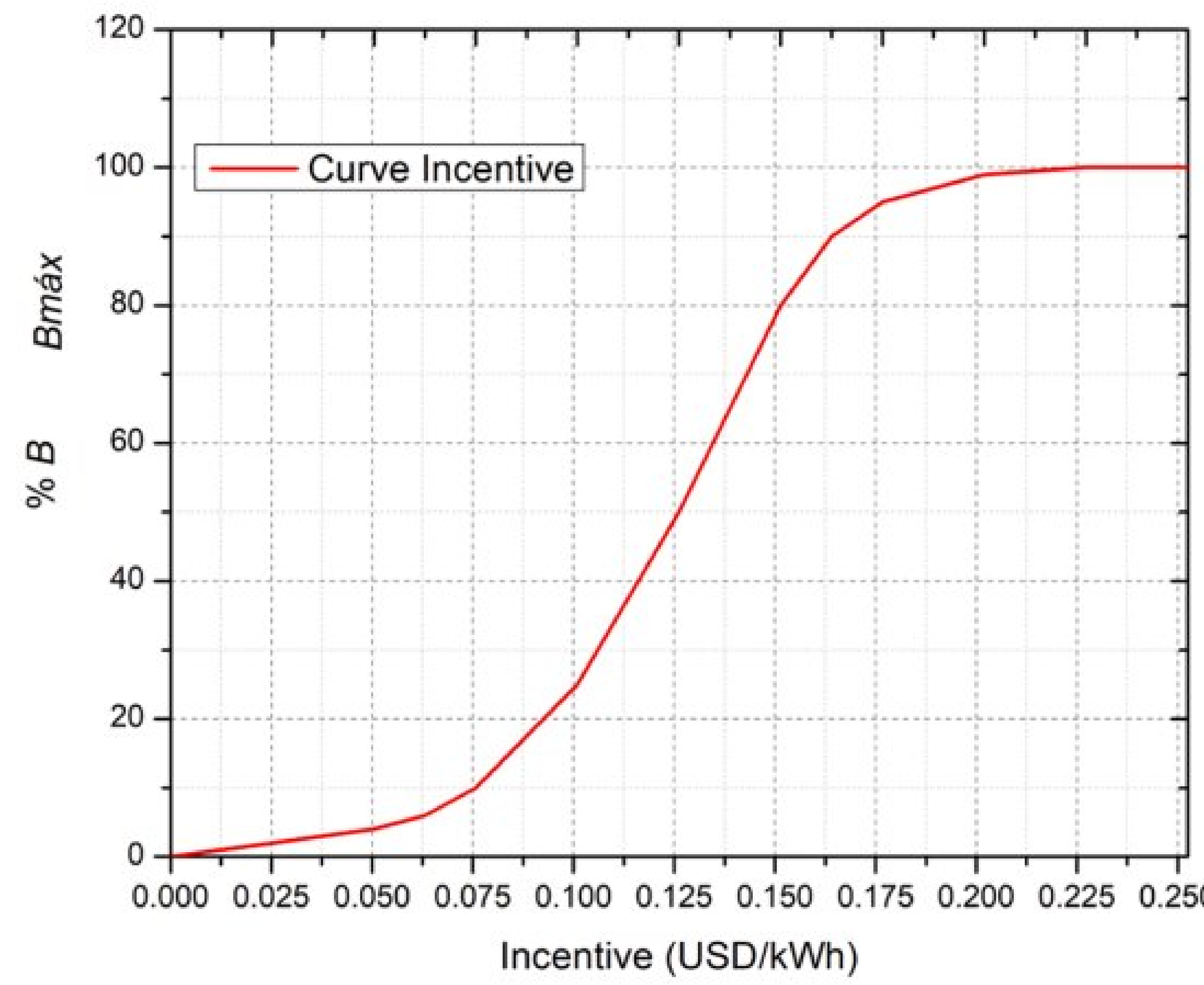

Fig. 1. Incentive-load participation characteristic.

$$Bmáx = \alpha t. Dmax\, t \tag{4}$$

Where:

β^{max} = demand sensitive to price and incentive variations at time t
$\alpha_{t,}$ = Ratio of price and incentive-based charges to total demand at time t
Dmax t = Total electricity demand at time t [MW].

Depicted to the cost savings It stabilised an Equivalent Unit Cost of Electricity as a function of the reduced consumption from implementing the DR TOU+INC model. The variance between the energy reductions brought about by the economic incentive and the actual consumption is determined using Eq. (5). The outcomes are presented in Table 1.

$$\mathrm{EUCi} = AUCi - AUCi.(ER)/AC \tag{5}$$

Where:

EUCi= Equivalent Unit Cost in period i
AUCi= Actual Unit Cost before DR in period i
ER= Energy reduction or savings target after DR
AC= Actual Consumption before DR

3.3. Energy demand forecasting model

The ARIMA model uses data variations and regressions for trend forecasting. It analyzes past time series data to forecast and control outlier values [28]. This technique is employed to analyze the historical energy demand in Miraflores, Guaviare.

The model is formulated and adjusted through the following stages. a) Identification: This involves determining the appropriate energy consumption data to replicate the time series. b) Analysis and differentiation of the time series to assess stationarity. c) Adjustment of the ARIMA model to establish stationarity. d) Prediction: In this final stage,

Table 1
Elasticity matrix.

(i,j)	Peak	Off-Peak	Valley
Peak	-0.1	0.016	0.012
Off-Peak	0.016	-0.1	0.01
Valley	0.012	0.01	-0.1

the goal is to probabilistically forecast the future behavior of the variable of interest. We use the statistical programming language R and its computing environment to simplify the development of the predictive model.

4. Scenarios formulation

4.1. Numerical simulation

The proposed multi-period mathematical model's functionality is evaluated in four scenarios by applying the TOU and TOU+ INC models. To do this, the baseline demand curve, or a daily average of the Miraflores municipality in the Guaviare department, is used, as illustrated in Fig. 2.

An approximate average electricity price of USD 0.36/kWh is considered, corresponding to the average electricity tariff for the first quarter of 2023 applied to the residential sector of the municipality [29–33]. For analytical purposes, the demand curve is divided into three periods: the off-peak period (11:00 pm to 10:00 am), the valley period (10:00 am to 7:00 pm), and the peak period (7:00 pm to 11:00 pm), and electricity prices of USD 0.30, USD 0.33 and USD 0.41/kWh are established in advance for each of these periods; These prices represent the electricity rates that a generating agent can offer to a consumer user to promote the non-existent price elasticity of electricity demand in Miraflores, as well as the displacement of energy consumption from periods with high electricity prices to periods with lower electricity prices.

The elasticity matrix requires the values of self-elasticity and cross-elasticity, as used in various DR programs for the residential sector [17] and in off-grid regions, as indicated in Table 1. These values of elasticities indicate demand sensitization in a respective period (i) to variations in the price of electricity in the remaining periods (j)

In the TOU+INC model, users receive economic incentives of USD 0.1/kWh in peak hours (30 % of average cost) and USD 0.07/kWh during maximum solar radiation hours. This aims to promote self-generation and the use of non-conventional renewable energy sources at the residential level.

The effects of demand response (DR) on energy demand behavior are analyzed based on prices and incentives in the following scenarios.

- ***Scenario 1***

When applying the TOU model to 100 % diesel energy consumption, the following are considered: i) Sensitivity only to energy consumption with electricity price increases during peak hours. ii) Sensitivity to energy demand during valley, peak, and off-peak periods due to changes in electricity prices.

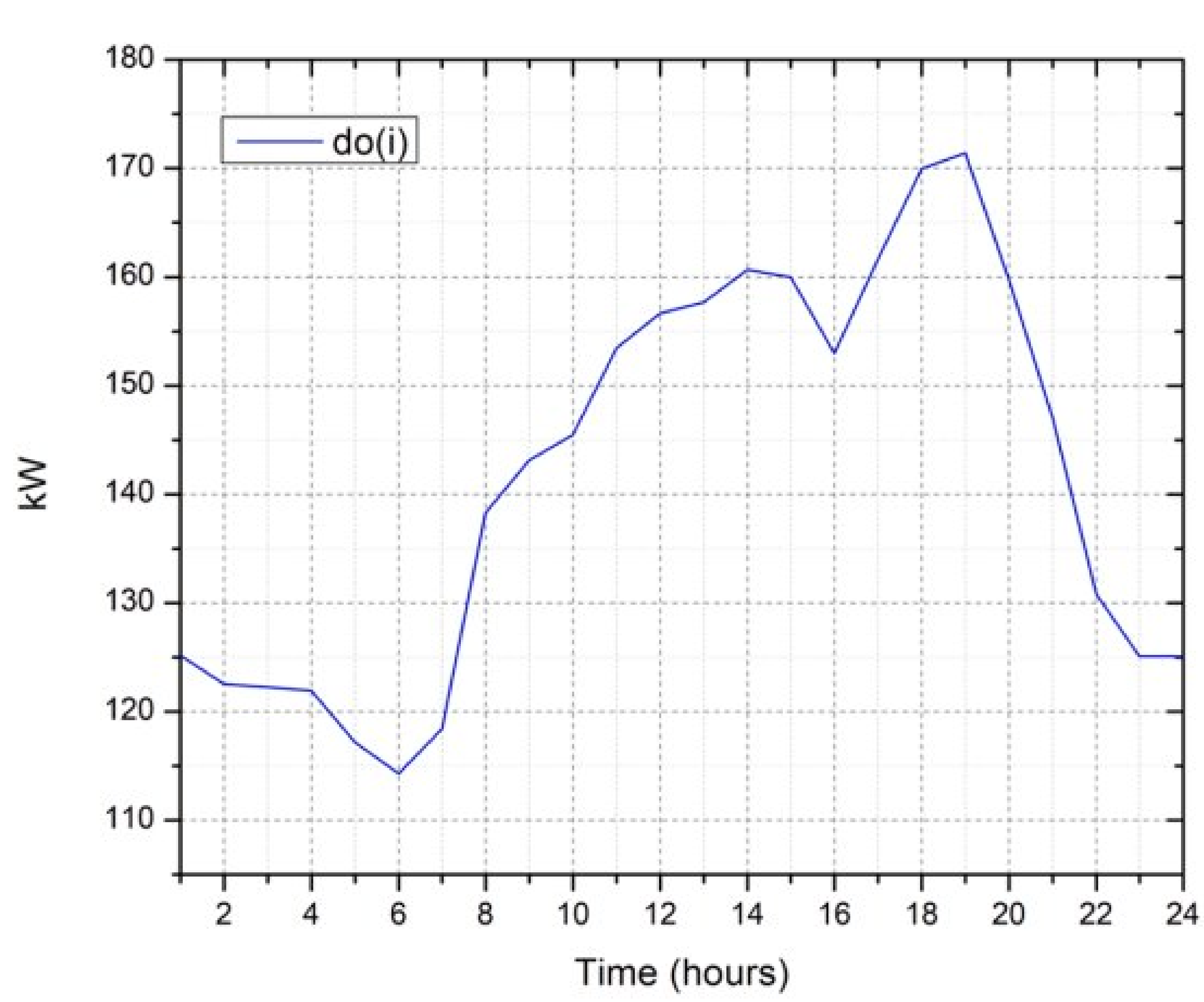

Fig. 2. Reference curve Miraflores Consumption.

- ***Scenario 2***

Application of the TOU+INC model to energy consumption with the participation of economic incentives at an electricity price of USD 0.1/kWh at peak solar radiation hours, i.e., from 10:00 am to 3:00 pm and electricity prices set in advance of USD 0.30, USD 0.33 and USD 0.41/kWh in off-peak and peak hours.

- ***Scenario 3***

Incremental incentive recognitions and their respective percentages of consumption reduction during peak hours are assumed as a consumer response based on the proposed S-curve, as shown in Table 2. The electricity prices and conditions of scenario two are maintained.

- ***Scenario 4***

The ARIMA model analyzed valley, off-peak, and peak electricity prices: USD 0.30, USD 0.33, and USD 0.41/kWh, respectively. A comparative forecast of energy consumption based on the application of the TOU+INC model was conducted using the following steps: a) Identification and organization of appropriate data to reproduce the time series, b) Evaluation of the stationarity of the time series using the Dickey-Fuller metho. Stationarity refers to the property of a time series where the statistical properties such as mean, variance, and autocorrelation remain constant over time. c) Determination and adjustment of the ARIMA model through the application of differences and logarithms to achieve stationarity, d) Predictive capability of the model. Historical energy consumption values are provided in Table 3, serving as a baseline for the project until 2024 [34].

5. Results

Regarding scenario No. 1 option i), when the TOU model is applied, there is a decrease in energy consumption during peak hours in response to the increase in the price of electricity from USD 0.36/kWh to USD 0.41/kWh at times of peak demand, as shown in Fig. 3.

The reduction in consumption induced by the application of the model is approximately 52.5 kWh/day, as shown in the comparison in Fig. 4. This result addresses the issue of the current generation capacity of Miraflores being oversized, as it currently meets peak demand periods with only 45 % of its nominal capacity [35]. This inefficient scenario leads to higher diesel fuel consumption and high operating temperatures [36]. In this sense, applying the Demand Response (DR) model would generate savings of approximately eight gallons/day in this scenario, based on the specific fuel consumption methodology established in [37] and the current installed diesel capacity.

Now in option *ii* of the same scenario, adjusting electricity prices during different times of the day resulted in a change in consumption of approximately 228 kWh, as shown in Fig. 5.

This change was not proportional to the decrease in consumption, as shown in Fig. 6, indicating that the mathematical model reacts to increased energy consumption by setting prices below USD 0.36/kWh. To address this, it is suggested that differential tariffs based on hourly segments be implemented to optimize energy consumption and promote energy savings for each user. These tariffs would significantly impact the current off-grid energy market in Miraflores.

Table 2
Percentage change in incentives vs. variation in load sensitivity.

INC (USD/kWh)	0.0875	0.1125	0.1375	0.150	0.2125
% Reduction	20 %	40 %	60 %	80 % *(Bmáx)*	100 %

Table 3
Historical monthly energy consumption data in MWh.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2018	60.7	58.8	64.8	58.0	64.5	59.4	65.0	69.1	72.2	73.8	77.0	75.8
2019	70.3	70.4	76.7	76.1	77.1	72.4	77.3	74.9	77.7	79.8	75.1	82.4
2020	78.1	78.1	83.1	76.3	77.5	74.0	75.0	75.0	75.0	79.3	80.2	77.8
2021	74.1	82.9	78.9	74.7	73.5	72.3	75.4	77.8	82.6	84.4	88.2	76.5
2022	80.3	89.1	84.4	90.3	83.2	84.0	83.4	85.4	86.3	85.2	84.4	86.2

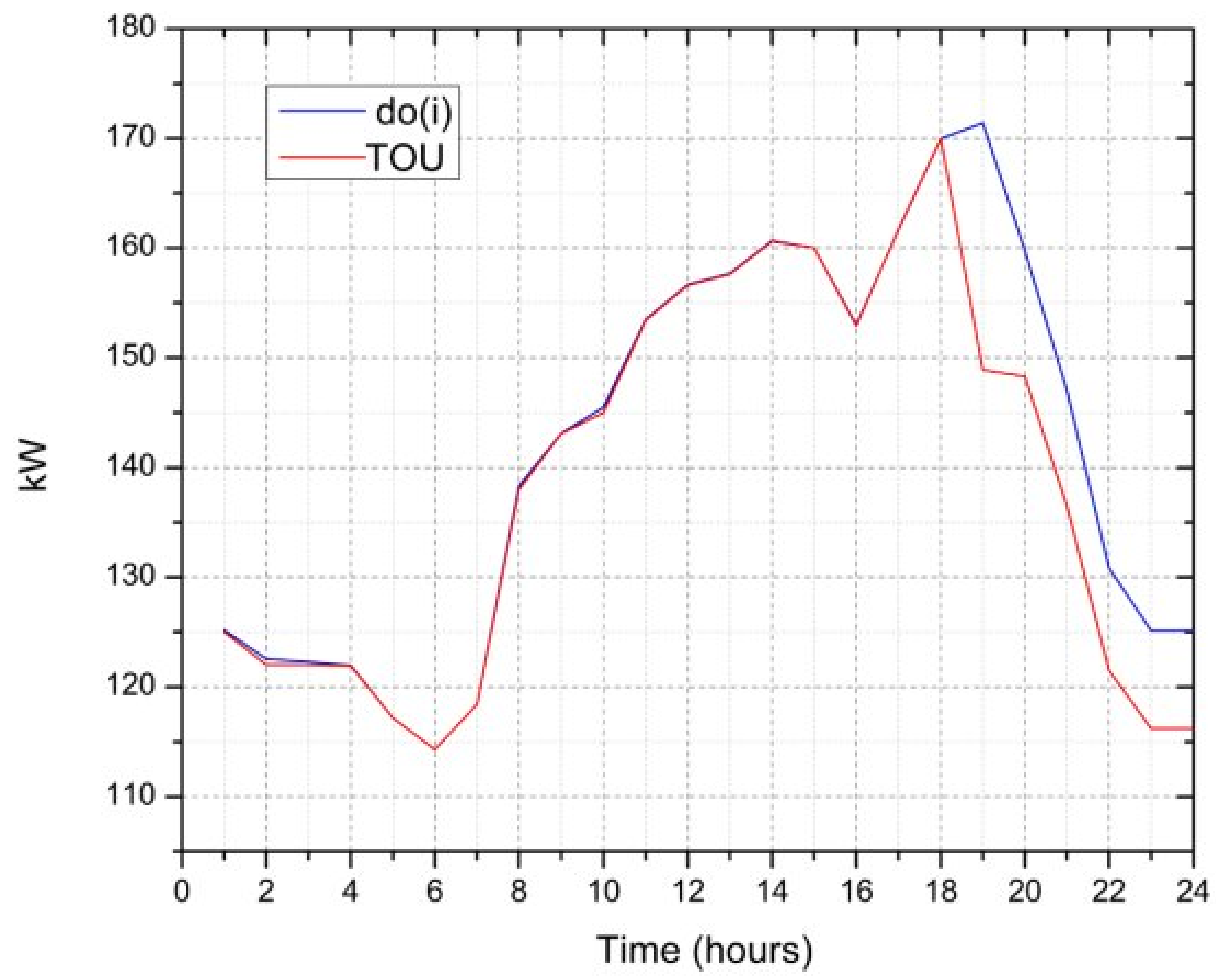

Fig. 3. TOU energy performance.

In scenario 2, when comparing the results between base consumption and recognizing an economic incentive of USD 0.1/kWh for the consumer from 10:00 am to 3:00 pm, Fig. 7 shows a substantial reduction in energy usage during this period, from approximately 941.5 kWh to 738.3 kWh.

Similarly, when comparing the results of the TOU and TOU+INC models, it is observed that for the same period, consumption is reduced from 842 kWh to 618 kWh. In Fig. 8, the DR models' energy consumption is compared with the base consumption, indicating a significant decrease in energy consumption that the consumer could compensate for without losing welfare in electricity use, using locally available renewable energy potentials such as solar radiation through self-generation [39]. From a tariff point of view, benefits are generated for the consumer in terms of monetary savings due to a decrease in invoicing; this decrease impacts a lower subsidiary burden, which is assumed by the state [38] (Table 4).

To analyze these results and identify and encourage energy savings, the consumption before and after applying the DR TOU +INC model is as follows: 941.5 kWh/day before and 738.3 kWh/day after. The difference

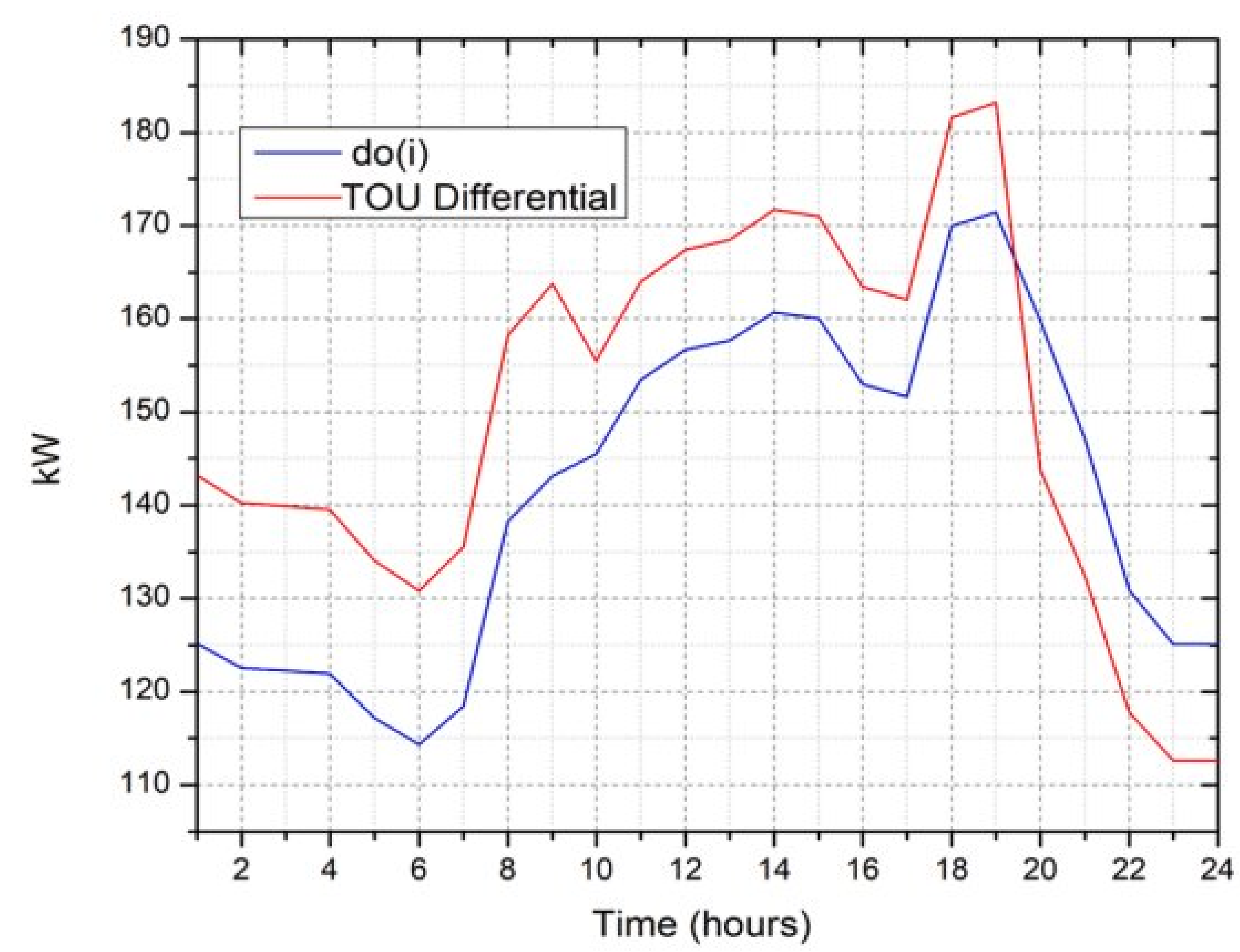

Fig. 5. TOU energy performance.

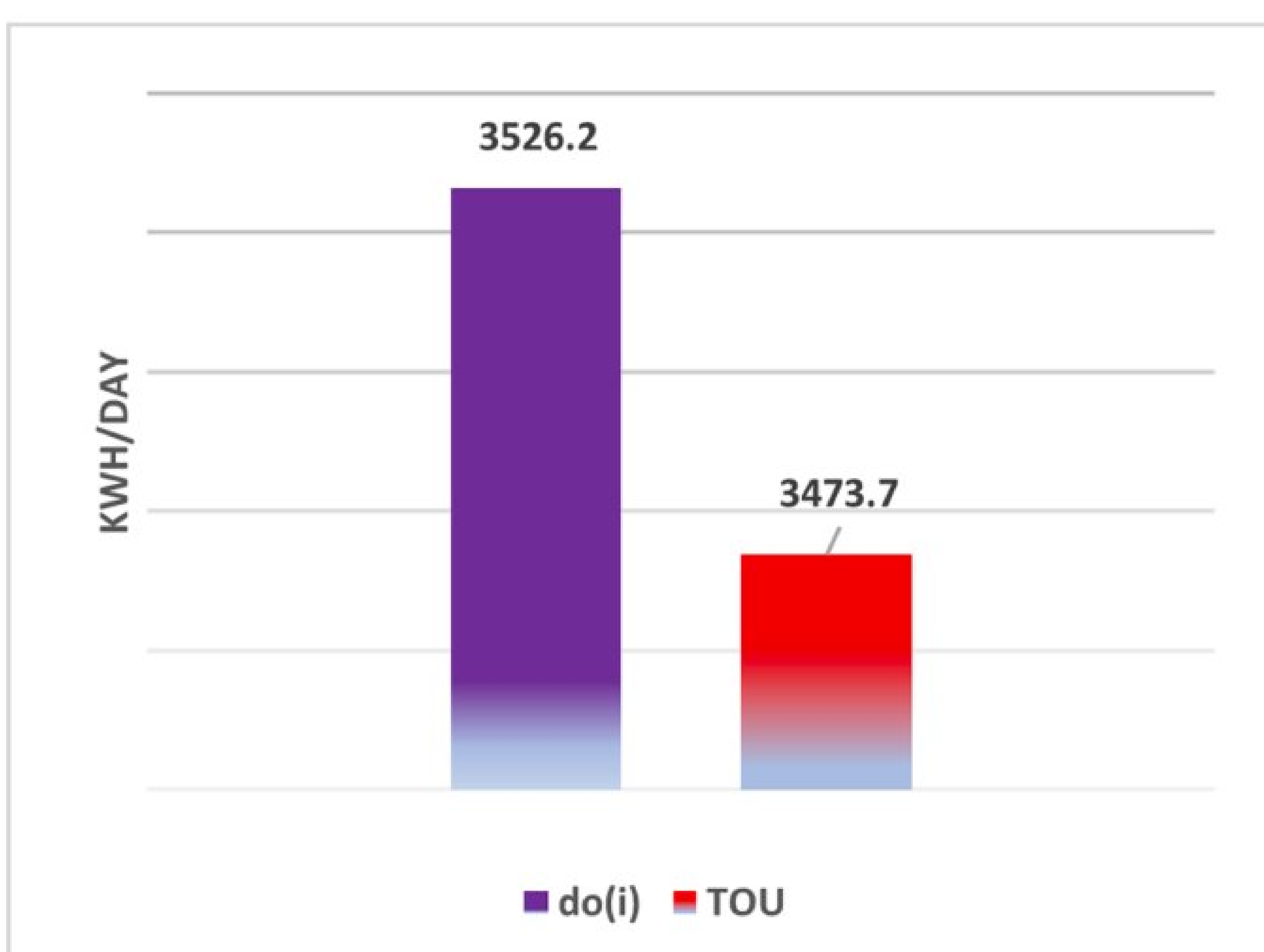

Fig. 4. DR Comparative.

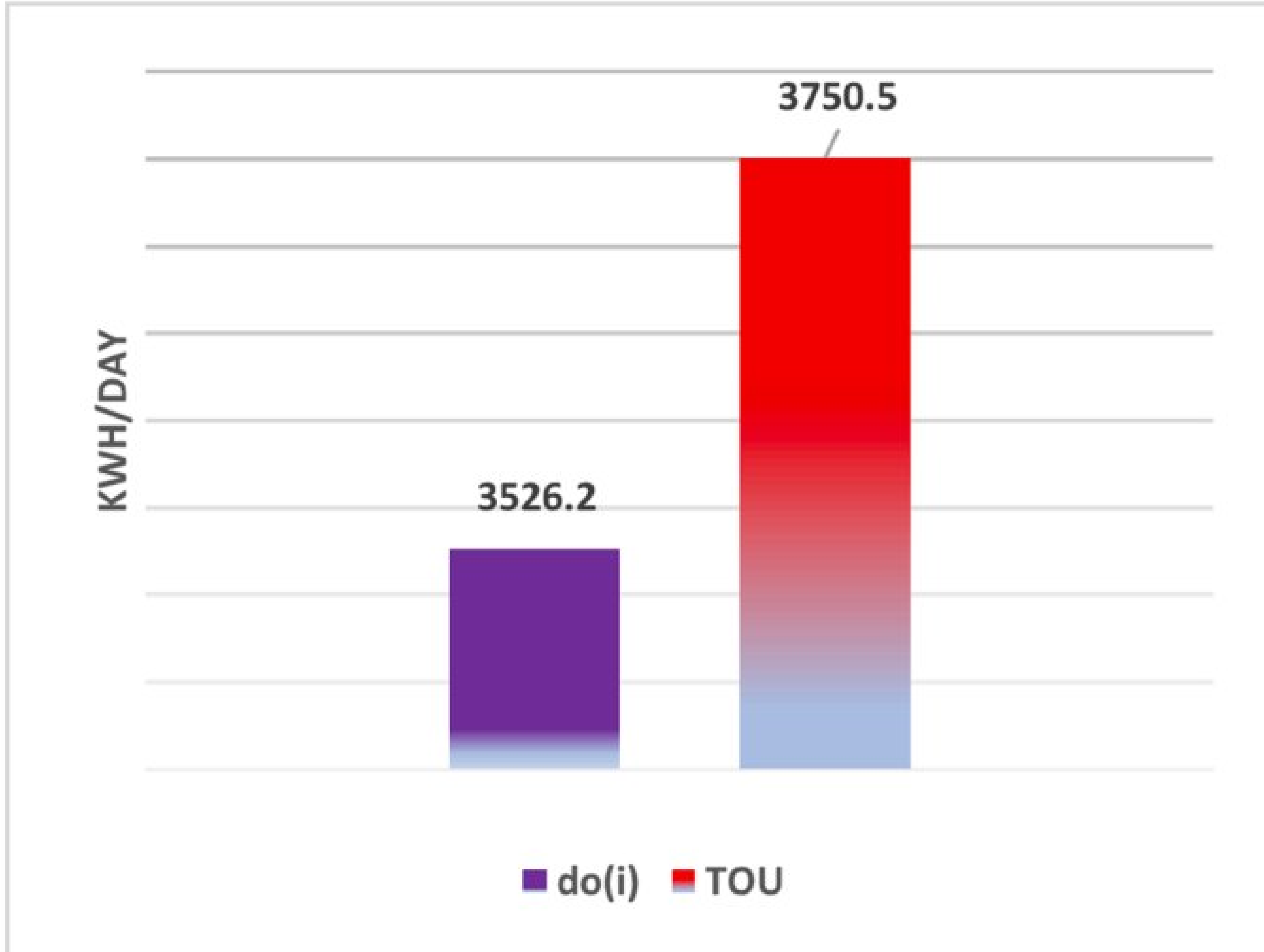

Fig. 6. DR Comparative.

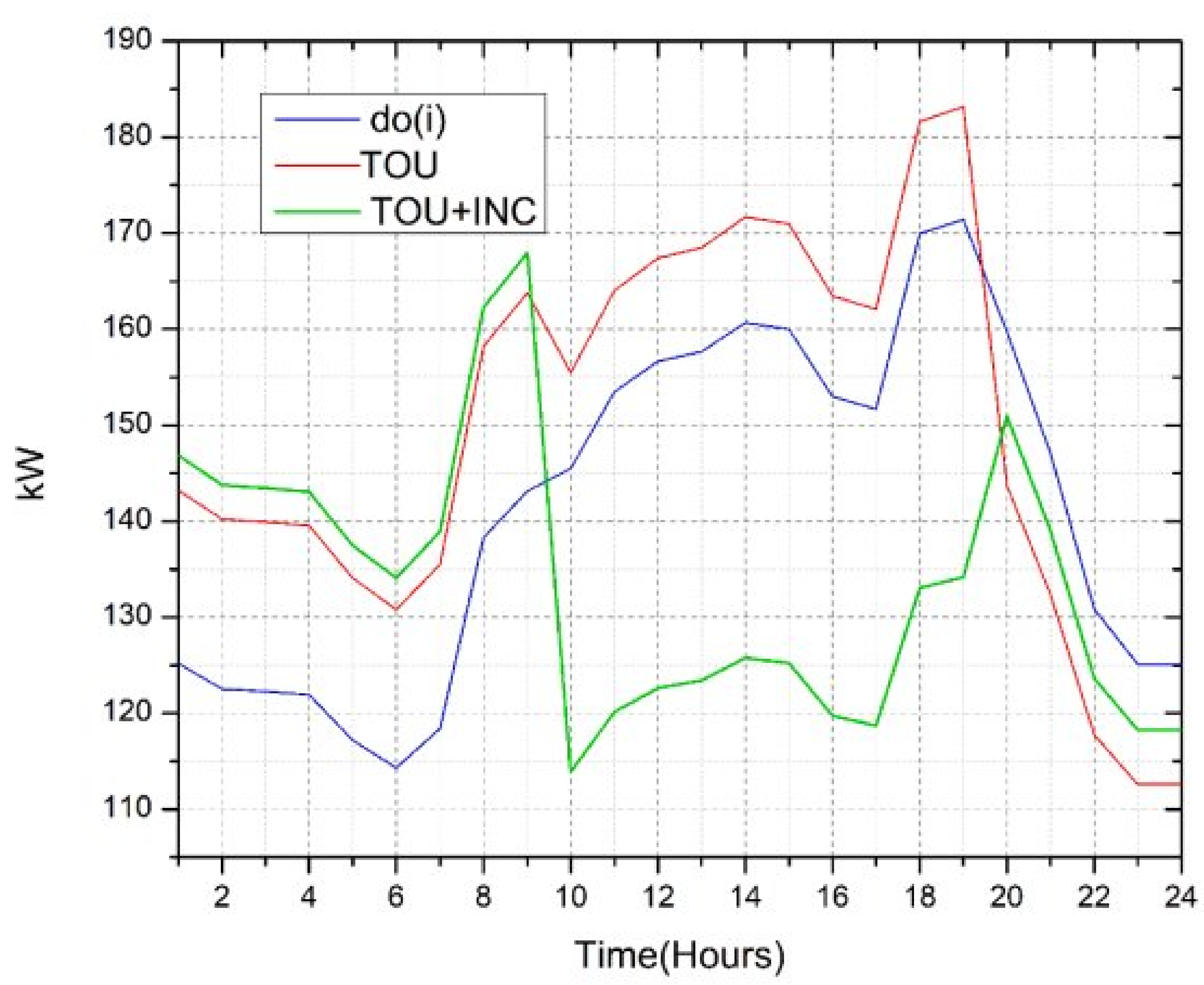

Fig. 7. TOU+INC energy performance.

of 203.2 kWh/day represents the overall savings of consumers who decided to accept the price signals of a generating agent. As a hypothesis, the reading of the energy measurement at the commercial border level is proposed, where the sum of the individual consumptions is registered. By reducing their consumption, they are granted a lower value to pay in their invoices. The savings from a global point of view are USD 119.5 per day.

In scenario 3, when differential incentives are applied during peak hours, the graphical results in Fig. 9 show the impact of the percentage change in economic incentives on the displacement and reduction of energy consumption per day.

The reduction in energy consumption is measured based on the findings in Table 5, indicating that a higher economic incentive in USD/kWh leads to more excellent responsiveness in Demand Response (DR), resulting in a more significant reduction in energy consumption when the incentive is implemented. To validate the results, comparisons are made with similar studies utilizing linear models, which have demonstrated benefits such as reduced consumption and optimized tariffs, among others [40].

In the context of scenario 4, the data representing the energy consumption baseline exhibits non-stationarity, as depicted in Fig. 10. This was confirmed through the application of the Dickey-Fuller statistical test. In the verification process, confidence intervals at or above 0.95 and a p-value of 0.05 were used as criteria. However, the obtained p-value of 0.0807 indicated the need for adjustments to the time series. To address this, the statistical differentiation technique was employed [41].

This involved formulating a hypothesis that the data's trend evolves slowly over time, requiring adjustments for each time point to be close to the previous one. Following this, a statistical p-value of 0.01 was achieved, signifying an appropriate seasonal adjustment of the time series and proximity of its data to a mean of zero, as illustrated in Fig. 11. Consequently, this paved the way for developing the ARIMA forecasting model.

After applying the ARIMA model to the adjusted time series, Fig. 12 displays the expected trend of energy consumption in the short term, specifically from 2023 to 2024. The monthly energy consumption forecasts, along with the lower and upper confidence limits of 80 % and 95 %, are presented in Table 6. For instance, the predicted energy consumption for August 2024 is 87,900 kWh. With 80 % confidence, the energy consumption is expected to range between 73,000 kWh and 102,100 kWh. With a 95 % confidence interval, the expected range is between 65,300 kWh and 109,800 kWh.

In this instance, there has been a noticeable rise in monthly energy consumption since the beginning of the first quarter of 2023. This increase can be linked to the growing trend of energy usage as indicated by historical data. Also, the necessary data to compile a 24-hour energy consumption record has been included. This is relevant because the current daily supply in the municipality of M18 hs is approximately 18 h [42].

When using the TOU+INC model to forecast energy consumption and applying the Dickey-Fuller statistical technique, the behavior and trend can be observed in Fig. 13, and the data is presented in Table 7. The energy consumption obtained is lower compared to the base consumption trend. For example, in August 2024, the predicted energy consumption is expected to be 85.100 kWh. With an 80 % confidence level, the energy consumption is projected to have a minimum value of 72.100 kWh and a maximum value of 97.800 kWh.

For a 95 % confidence interval, energy consumption is anticipated to have a minimum value of 65.300 kWh and a maximum value of 104.600 kWh. These results demonstrate the positive impact of applying the TOU

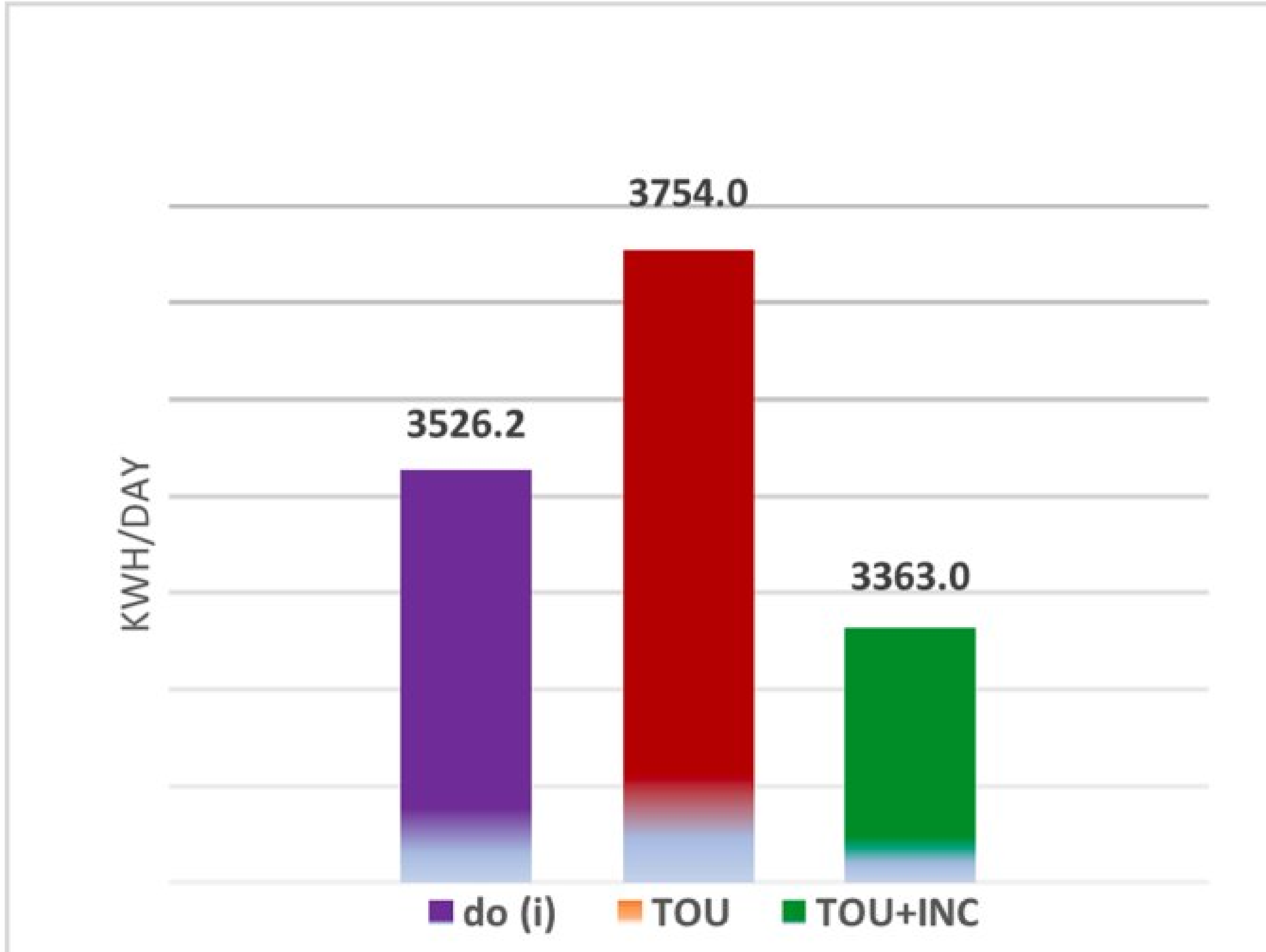

Fig. 8. Comparative DR.

Table 4
Equivalent UC results.

Parameters	Energy DR (kWh)	AC (kWh)	ER (kWh)	AUC (USD/kWh)	EUCi. (USD/kWh)	Billing with DR(USD)	Billing without DR(USD)
Results	738.3	941.5	203.2	0.33	0.26	191.2	310.7

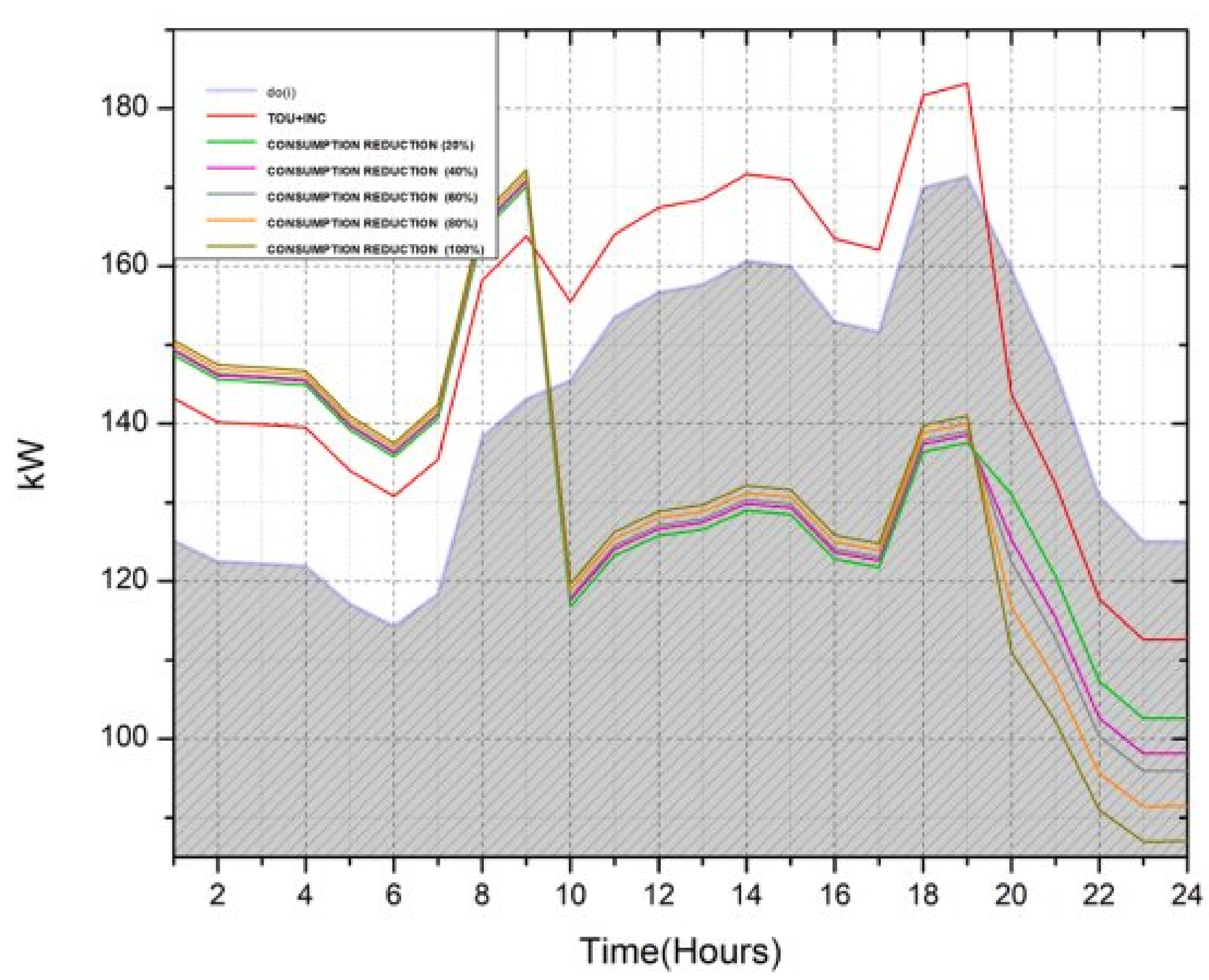

Fig. 9. Energy performance by incentive variation.

Table 5
Results decrease in consumption during peak hours according to the percentage change in economic incentives.

INC (USD/kWh)	0.0875	0.1125	0.1375	0.150	0.2125
% Demand	20 %	40 %	60 %	80 %	100 %
Reduction (kWh)	157.5	181.0	192.8	*(Bmáx)* 216.4	240.0

+INC model in reducing projected energy consumption, as illustrated in Fig. 14.

When considering CO_2 emissions reductions, it is essential to note that most electricity generation in Miraflores municipality uses diesel fuel. When converting emissions or energy data into an equivalent amount of carbon dioxide (CO_2) emissions using the Greenhouse Gases equivalence [43,44], the results in Fig. 15 show that applying the TOU+INC model keeps CO_2 emissions at lower levels compared to the scenario without DR implementation.

Reducing CO_2 emissions is crucial because it helps decrease the carbon footprint. This is discussed in [45] and [46] and is relevant to the off-grid areas of Miraflores, where most of the electricity generation is mainly from diesel sources.

5.1. Comparations and limitations

The TOU model offers several significant advantages in off-grid regions such as promoting energy efficiency, self-managing consumers to modify their consumption patterns according to set energy prices, reducing dependence on conventional sources, and boosting demand elasticity. However, some limitations may arise in the application of the Time Of Use model, for example, an inadequate signal of high electricity prices declared by a generating agent can provoke an uncontrolled displacement of demand towards periods of low electricity prices, which would imply important imbalances in the supply-demand balance in the respective period, however, this impact would be minimized with an appropriate determination of the maximum hourly flexible demand to be intervened [47]. Due to the linear nature of the proposed model, a proper formulation of restrictions is necessary according to the scenarios to be controlled.

From a technological perspective, the successful implementation of the TOU model depends heavily on an appropriate electrical infrastructure. In these off-grid regions, the limited availability of automated equipment for residential consumption, as in the case of Miraflores, Guaviare, leads to a limited reaction of consumers to pre-established electricity rates. Although limiting, this scenario encourages strategies to strengthen technological capabilities in these regions.

Comparing the results of the present research with other studies, [48] identified the effect of a time-of-use pricing scheme on residential electricity consumption in a rural region of Spain, using a so-called

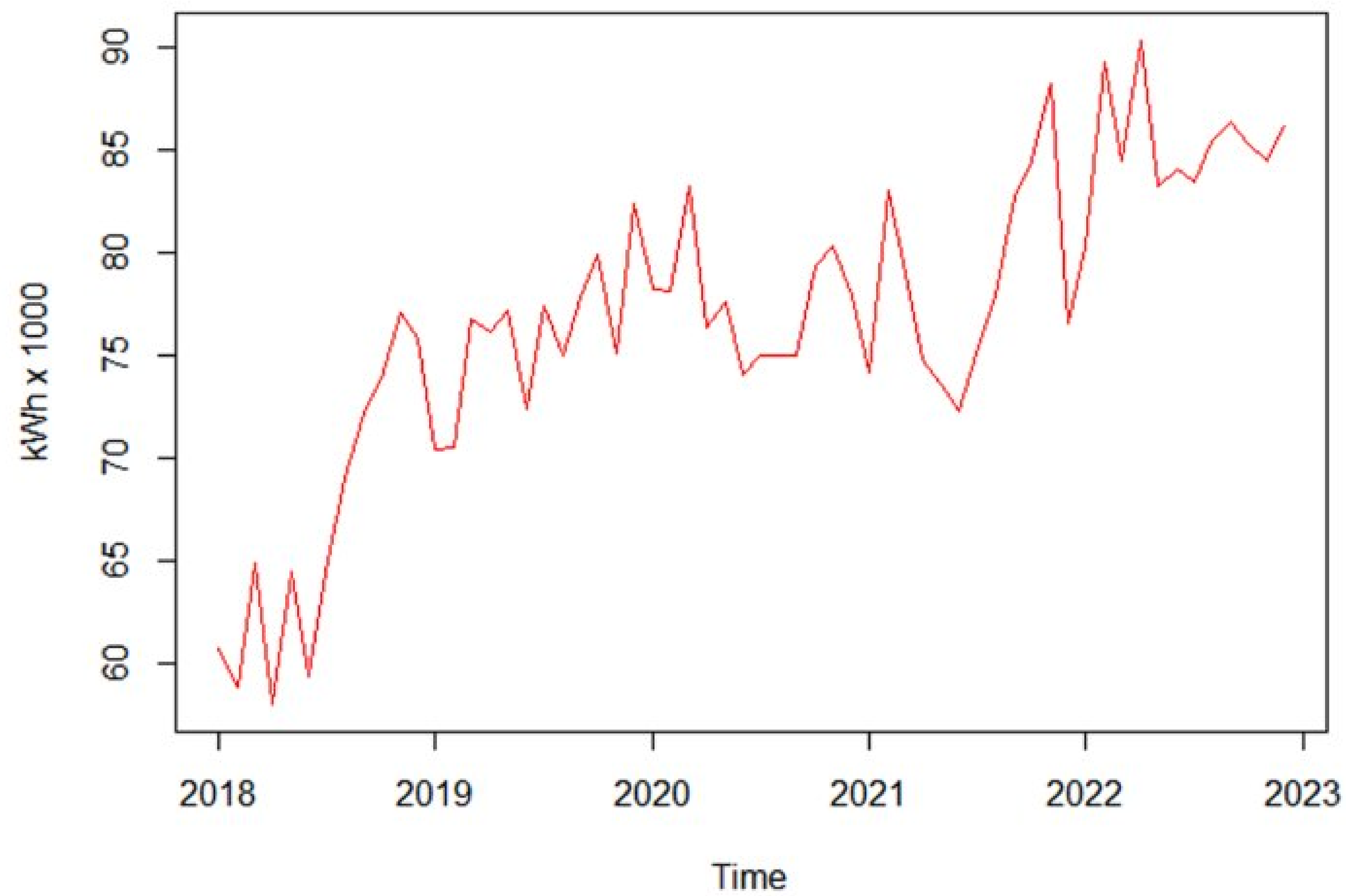

Fig. 10. Energy consumption. Time series basis.

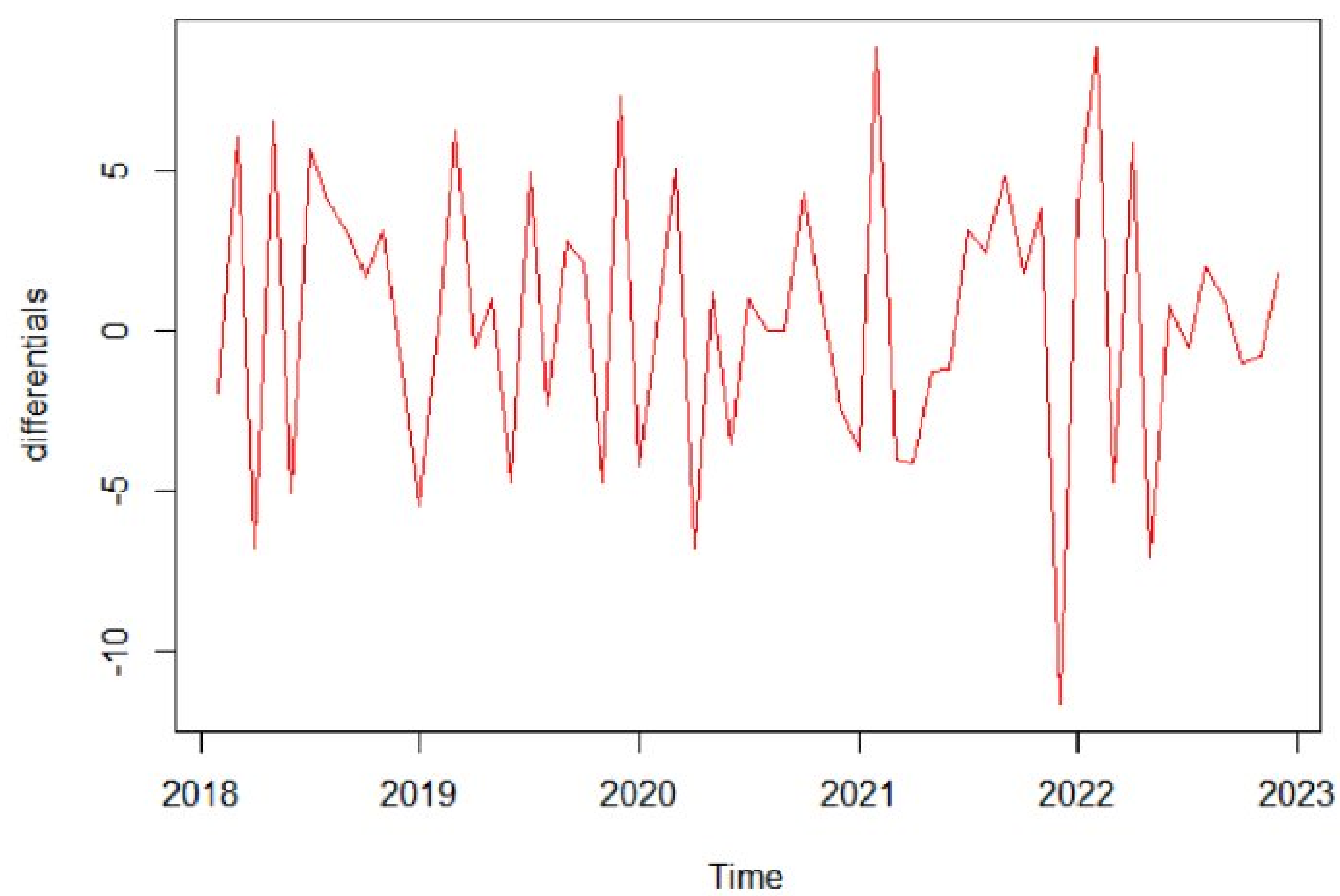

Fig. 11. Seasonality Time Series.

Difference-in-Difference approach, the results show that households responded by reducing consumption during peak hours by up to 9 %, which is similar to the results obtained from Figs. 3 and 4. The results suggest that a predetermined pricing scheme can improve consumer awareness and increase household price elasticity, making the TOU model an effective tool to reduce peak electricity demand and improve the efficiency of an electricity market. In [49] evaluated the results of a novel load-shifting approach for 300 residential virtual users based on TOU tariff and dynamic pricing conditions. The results indicate favorability and positive economic effects when applying the TOU model making visible its functionality as a means to validate load shifting strategies, obtaining peak demand reduction from 10,741 kW to 7369 kW, complementarily the applied TOU model managed to reduce residential tariffs by 12.17 %, similar results in the tariff reduction of the present study are related in Table 4. In [50] using a large-scale pilot test TOU pricing for residential customers, the effects of TOU pricing on residential customers' load patterns and producers' surplus in regions of South Korea were analyzed, The results found effectively reduced and shift energy consumption, generating billing benefits similar to the results obtained from Table 4, indicating that the TOU model is an effective measure to shift electricity consumption from periods with higher marginal cost of generation to those with lower marginal cost of generation. Although revenues tend to decrease, the cost savings are higher and the producer surplus increases. In [51] through a controlled trial in the Irish residential electricity market in Ireland comprised of 5000 households, the response of households at different times of the day was analyzed, when applying the TOU model there was a significant reduction in electricity consumption during peak hours, identifying favorable reactions with variations between 16.1 % and 37.1 %, similar results of the present study, where an approximate reduction of 21 % is observed in Fig. 3.

Concerning the possible regulatory, social, and economic obstacles that could arise in the actual implementation of the model, the main barriers that have been identified from the results of this research are as follows.

Regulatory barriers: The most relevant obstacle to the application in the Off-grid regions of Colombia is related to the regulatory aspect, due to the insufficient regulatory maturity for these regions. Although there are important advances in energy policies, such as the implementation of the energy transition law (2099 of 2021) that seeks to promote efficient energy management and demand response, the application for off-grid regions has not been regulated. On the other hand, in Colombia, the

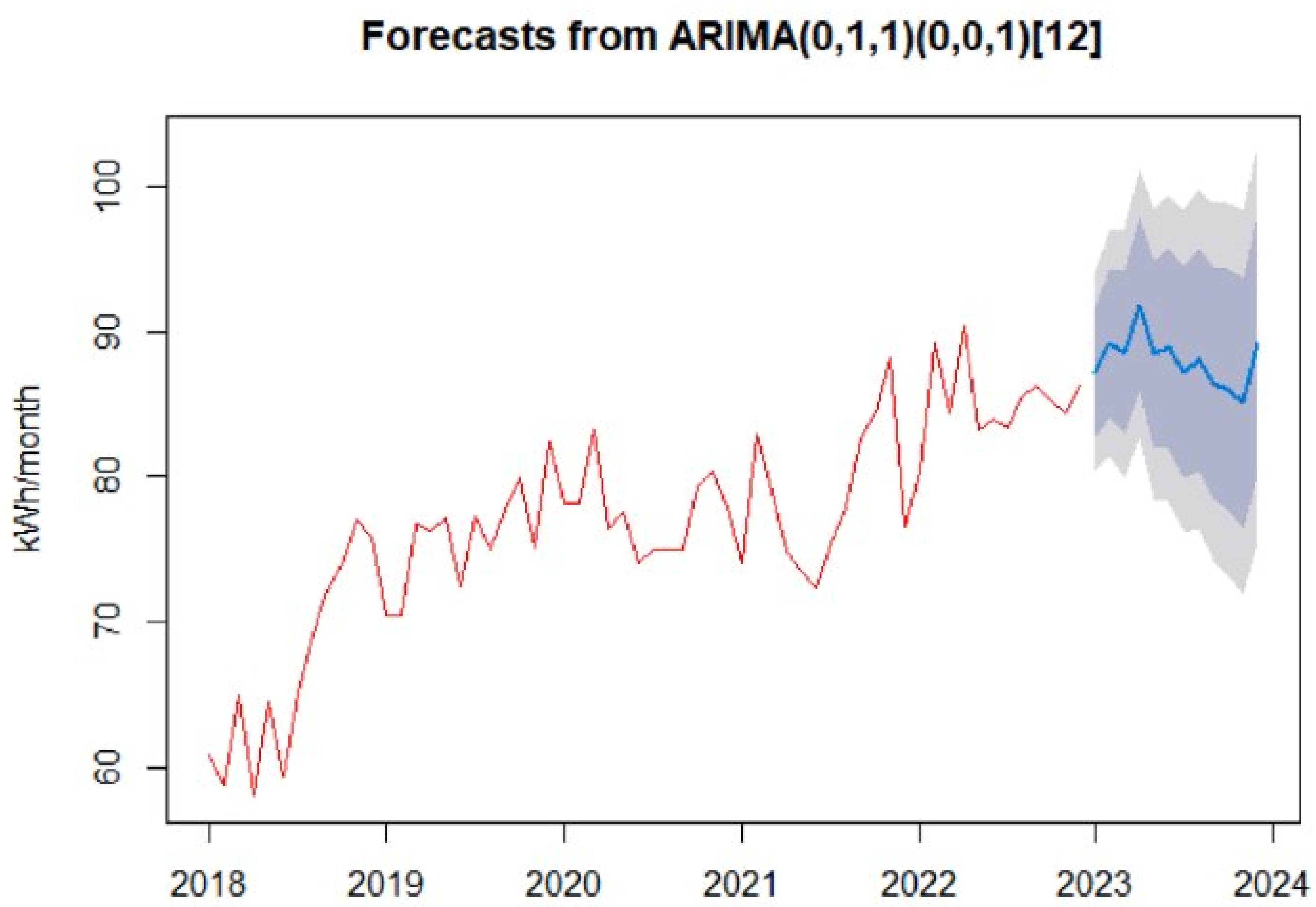

Fig. 12. Base energy consumption forecast.

Table 6
Energy consumption forecast results (Thousands of kWh) without DR.

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Apr 2023	91.8	85.8	97.9	82.6	101.1
May 2023	88.4	81.9	94.9	78.5	98.4
Jun 2023	88.9	91.9	95.8	78.3	91.4
Jul 2023	87.2	79.9	94.5	76.1	98.4
Aug 2023	88.0	80.4	95.7	76.3	99.7
Sep 2023	86.5	78.5	94.5	76.3	98.8
Oct 2023	86.0	77.7	94.4	73.3	98.9
Nov 2023	85.1	76.4	93.8	71.8	98.4
Dec 2023	89.3	80.2	98.2	75.5	102.9
Jan 2024	87.5	77.2	97.9	71.7	103.5
Feb 2024	87.6	76.5	98.7	70.7	104.5
Mar 2024	87.6	75.9	99.3	69.6	105.5
Apr 2024	87.7	75.2	99.9	68.7	106.5
May 2024	87.8	74.6	100.5	67.8	107.4
Jun 2024	87.8	74.1	101.6	66.9	108.2
Jul 2024	87.8	73.5	101.7	66.1	109.0
Aug 2024	87.9	73.0	102.1	65.3	109.8
Sep 2024	87.8	72.6	102.6	64.6	110.6

Table 7
Energy consumption forecast results (Thousands of kWh) with DR+INC.

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Apr 2023	91.2	86.9	95.6	84.6	97.9
May 2023	87.6	82.7	92.4	80.2	95.0
Jun 2023	88.0	82.7	93.3	79.9	96.1
Jul 2023	85.5	79.7	91.2	76.7	94.3
Aug 2023	86.8	80.6	92.9	77.4	96.2
Sep 2023	84.2	77.7	90.8	74.3	94.2
Oct 2023	83.9	77.0	90.8	73.4	94.4
Nov 2023	83.2	75.9	90.4	72.1	94.2
Dec 2023	88.3	80.8	95.9	76.8	99.8
Jan 2024	88.4	80.6	96.3	76.5	100.4
Feb 2024	84.2	76.0	92.3	71.7	96.6
Mar 2024	84.2	75.8	92.6	71.3	97.1
Apr 2024	85.0	74.8	95.1	69.4	100.5
May 2024	85.1	74.1	95.8	68.3	101.6
Jun 2024	85.2	73.4	96.5	67.2	102.7
Jul 2024	85.0	72.7	97.2	66.2	103.7
Aug 2024	85.1	72.1	97.8	65.3	104.6
Sep 2024	85.0	71.5	98.4	64.4	105.5

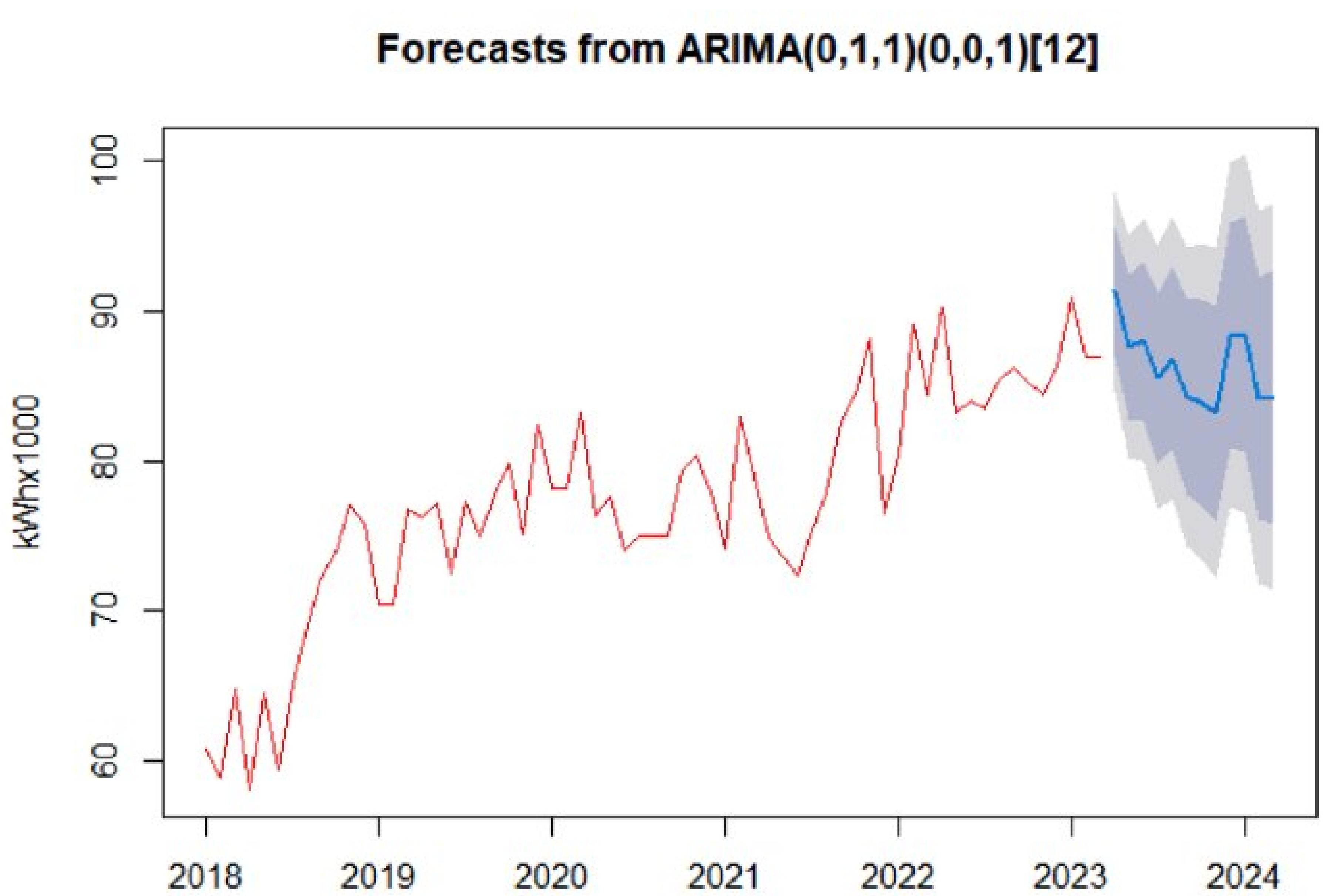

Fig. 13. Energy consumption forecast for application of DR TOU+INC.

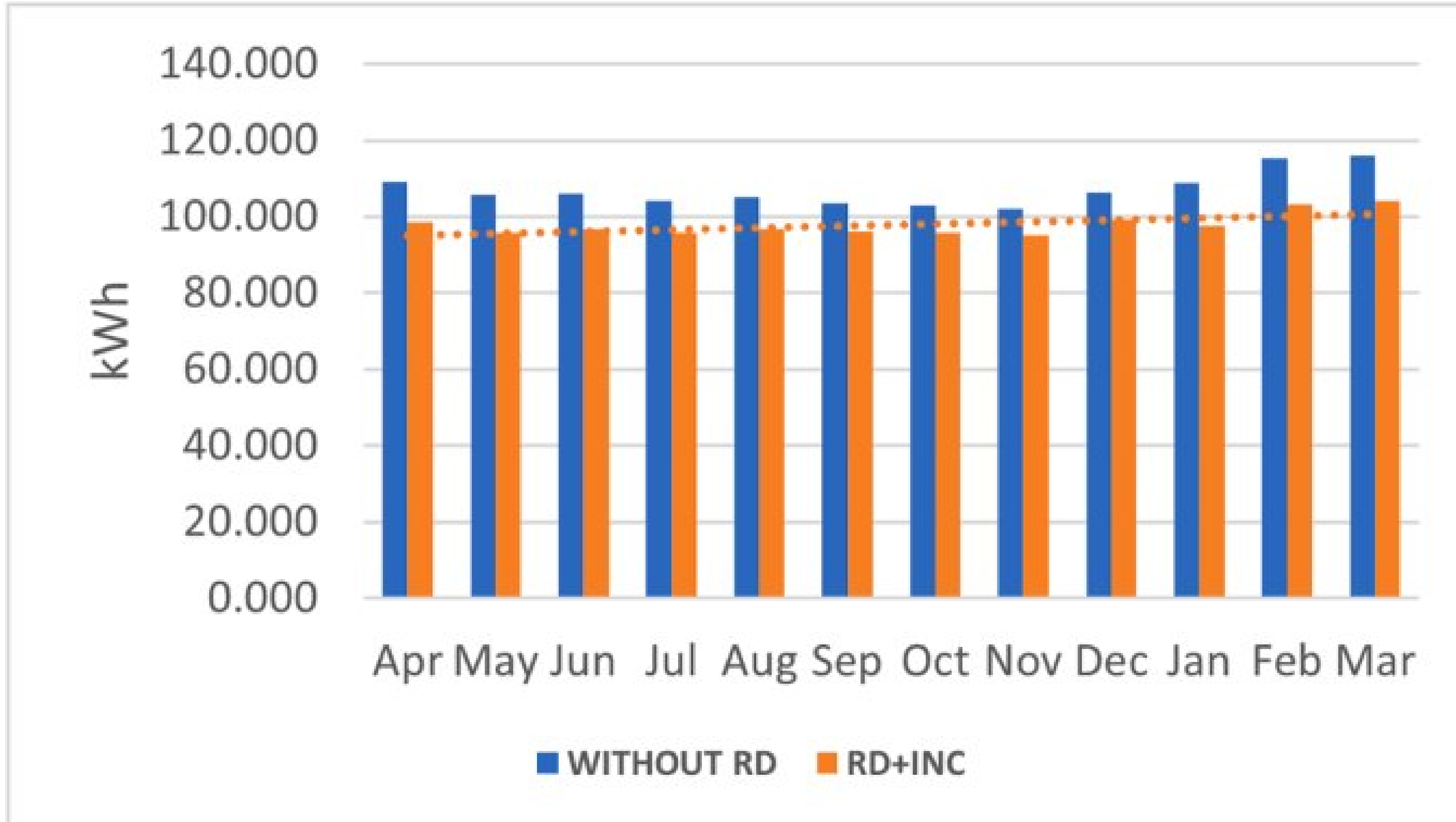

Fig. 14. Comparative energy consumption Forecast 2023–2024.

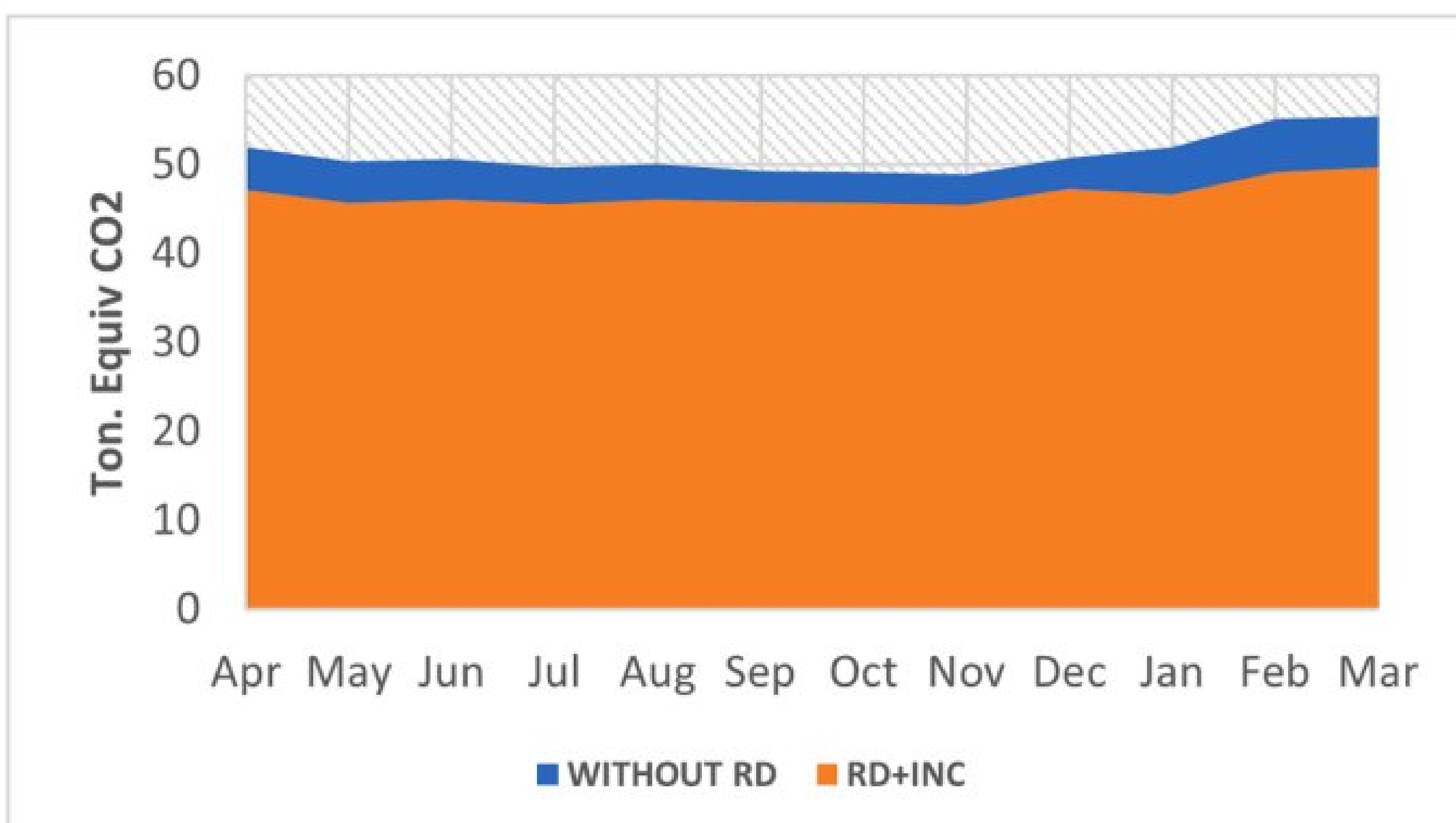

Fig. 15. Comparison of tons of CO_2 forecast energy consumption 2023–2024.

Energy and Gas Regulatory Commission has developed a Roadmap for Demand Response (document CREG 001–2022), however, its application environment is the regions connected to the Grid. One strategy to encourage policymakers is to spread the benefits to communities and raise awareness about them. These benefits include lower energy bills, improved environmental quality due to reduced CO2 emissions as illustrated in Fig. 15, decreased energy subsidies by the state, and reduced reliance on diesel fuel for electricity generation in these regions where about 84 % of capacity comes from that source Economic barriers: When communities are low-income, consumption habits may not be amenable to change, leading to disparities in access to the benefits of the TOU model.

5.2. Financial implications

To analyze the long-term financial repercussions from the demand side when comparing the results and incentivizing energy savings, consumption before and after applying the DR TOU + INC model is 941.5 kWh/day and 738.3 kWh/day respectively. The difference of 203.2 kWh/day represents the global savings of consumers who decided to accept the price signals of a generating agent. According to the results of Eq. 5 and Table 4 in a 5-year horizon, the billing savings are USD 119.5 per day equivalent to USD 215,100 indicating a high level of probability on the time horizon of a positive financial impact. On the other hand, due to the geographical and remote characteristics of off-grid regions [34] likely, the implementation costs of the TOU model and the associated technologies incurred by suppliers will increase the initial investment costs, causing longer recovery periods. This financial impact can be minimized by taking maximum advantage of renewable resources locally and incorporating efficient technologies [48]

5.3. Discussions

From the results obtained in the application of the TOU model for the four scenarios, potential benefits for consumers and communities are evident. Regarding consumers, as illustrated in Table 4, the decrease in energy consumption by 203.2 kWh/day led to a reduction in monthly energy bills, in that sense the expectation of a materialized reduction promotes consumer participation in informed decision-making and boosts predictability in energy expenditure. From the technological point of view, although it is not a topic that is developed in this research, intelligent and automatic equipment is necessary for the management of demand response for consumers to make informed decisions; this articulation promotes new knowledge in the communities of the regions not connected to the grid. To the results in Fig. 7 and Fig. 8 where energy consumption was reduced from 941.5 kWh to 738.3 kWh and from 842 kWh to 618 kWh by applying the TOU and TOU +INC models respectively, consumers benefit from the reduction in their bills and stimulating the use of renewable energies.

In terms of the benefits to communities, the results show that the TOU model is a great articulator that promotes community cooperation by identifying that individual benefits can be achieved by all members of a community benefiting from differential tariffs in the off-peak, peak, and valley segments. About consumer participation strategies, the document is characterized by a technical study, the origin of the impact of the TOU model originates in the generation offer formulated by the generating agent to the community who make decisions to accept the price signals and incentives based on the benefits it represents

6. Conclusions

Throughout our ongoing research, we have noted a significant increase in the volume of literature concerning Demand Response management from the standpoint of consumers. Additionally, the research has brought to light the favorable impact of this approach on reducing energy consumption. The findings suggest that offering economic incentives, such as price signals to consumers, encourages changes in energy consumption patterns, including load reduction and load shifting. This cost-effective approach reduces energy consumption and CO_2 emissions, lowers diesel fuel consumption, and decreases electricity prices. In contrast, Colombia's current energy market in off-grid regions does not have differentiated tariffs. Introducing economic incentives could be an opportunity to propose a new tariff model that shifts from static tariffs to dynamic ones. In a simulated scenario, we investigated the impact of demand elasticity on short-term energy consumption in the municipality of Miraflores. This was accomplished by utilizing the TOU+INC model, which resulted in a noteworthy reduction in energy consumption and projected displacement. Furthermore, upon comparing the projected emissions with the base case, we observed a substantial decrease in CO_2 emissions by employing the TOU+INC model. These results indicate a promising avenue for greater compliance with emissions reduction commitments and energy efficiency regulations. Given the unique conditions of the NIZ, including the limited ability of residential users to make payments, the scarcity of efficient technology for electricity use, and the lack of awareness about the advantages of Demand Response, it is crucial to delve deeply into these aspects to mitigate the risks associated with transitioning to a new energy market based on demand management.

The modeling and validation of the energy demand behavior in the municipality of Miraflores by incorporating demand response (DR) programs, specifically the TOU model with the addition of incentives (TOU + INC), provides an opportunity for this approach to be replicated in other non-interconnected areas with similar energy characteristics to those of Miraflores. The cost of electricity plays a significant role in determining consumer behavior in off-grid regions. Under current energy market conditions, differential pricing notably impacts the decision-making process regarding electricity consumption at specific times. This has been demonstrated by applying the TOU and TOU+INC models, indicating that varying electricity prices influence consumption behavior across different time segments. The flexibility of Demand Response allows it to work well with the varying energy supply from renewable sources, which depends on the weather conditions. This means energy consumption can be shifted from peak to off-peak periods when renewable energy production is higher. As a result, this can help manage generation costs over time, leading to more favorable electricity prices and the potential for implementing hybrid energy systems.

Regarding regulations, distributed renewable energy is well positioned for growth in off-grid areas. For example, Decree 388 of 2016 from Colombia's Energy and Gas Regulatory Commission allows for adjusting existing tariff formulas to create a unique scheme that encourages consumers to save energy.

Although communication strategies for appropriate price signaling are not developed in this investigation, appropriate communication between a network operator and consumers can be achieved through mobile applications, programmed mass outreach campaigns, SMS messages, call centers, as well as websites. On the other hand, through monitoring and smart metering, consumer participation and adaptation to hourly tariffs can be achieved.

Regarding the elasticity of demand, its adhesion to the real world depends mainly on some variables such as economic, social, and behavioral variables of each user. It is necessary to make a gradual process of evaluation of the incidence of these variables in the result of the TOU model, which would add a new dimension to the present research and be developed in future works.

CRediT authorship contribution statement

J.A. Valencia: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **I. Dyner:** Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology. **F. Mesa:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Investigation. **A.J. Aristizábal:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis.

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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Data availability

No data was used for the research described in the article.

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