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Original article

# A technical and economic approach to multi-level optimization models for electricity demand considering user-supplier interaction

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ABSTRACT

One-level optimization methods have been proposed to optimize a single user's load profile or a cluster of users in the smart grids. In this work, two two-level optimization methods are studied, one case considering technical requirements (case 1) and another considering economic criterion (case 2). In the upper level, the supplier optimizes the objective function. Meanwhile, at the lower level, users optimize their electrical costs. The proposed methods are based on Genetic Algorithm methods. In this sense, an indirect control is established in which users react to a price signal. Simulation results illustrate that both cases improve the demand profile and increase the retailer profit concerning an unscheduled case. However, when the supplier tries to maximize the profit, some users receive benefits to detriment of others, concluding that the technical approach is preferable to the economic one.


## 1. Introduction

Historically, power systems have been vertically governed by clearly defined subsystems: generation, transmission, and distribution. However, how energy is consumed, transported, and produced is drastically modified by incorporating new technologies such as Distributed Generation (DG), distributed storage, and electric cars. In consequence, control and operation systems and demand-side management (DSM) are spread over the distribution networks (Bragagnolo et al., 2020; Subasic, 2015). In these contexts, the smart grid (SG) concept emerges and, although it is still in development, it is becoming a reality in the world's electric scenario. SG represents the union of computation, automation, and communication technologies applied to the monitoring, control, and maintenance of electrical grids. It enables a more sustainable, reliable, and secure electrical power supply. However, its implementation requires modifications in the current network such as the installation of sensors, data processors, communication services, and changes in the energy market. Its main functions are to motivate customer participation, increase service quality, integrate DG, and energy storage (Vidal et al., 2014). The SG collects information via modern communication technologies that provide efficiency, reliability, and cost-saving energy generation and distribution. SG comprises generation, distributed generation, transmission, distribution, and consumption (Belhaiza and Baroudi, 2015).

Electric power systems deal with different challenges, such as reliability problems, low efficiency, high energy losses, high emissions, and high market power. On the demand side, the traditional flat electricity tariff represents a disconnection between the wholesale electricity market price and retail tariffs. It leads to inefficient use of resources, as consumers have no motivation to adjust their use (Jordehi, 2019; Mahmoud et al., 2010). Moreover, partly driven by the need for decarbonization, the use of electric heating with heat pumps, electric vehicles, and the incorporation of DG will increase considerably. Besides, the demand becomes more fluctuating and with higher peaks, reducing generation efficiency, increasing grid losses, and the associated electrical costs (Gardumi, 2016; Kassakian et al., 2011; Molderink et al., 2010). Based on these changes, supply–demand balancing in electricity grids, to ensure reliability and quality, becomes a more complex problem. To deal with these challenges, there is great interest in DSM, as well as in the storage of excess power generation (Yilmaz et al., 2019). The DSM allows flatting the demand curve, reducing losses due to energy dissipation produced by power system lines.

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**Nomenclature**

| | | | |
|---|---|---|---|
| A | State Matrix | Epc | Energy consumption of all users |
| E | Energy Consumption Vector | ΔE | Flattening factor |
| X | User demand strategy | gi | Supplier constraint function |
| P | Price Vector ($/Wh) | C | Cost of electricity supply |
| B | Electricity bill ($) | | |

There are two main DSM approaches: indirect control or direct control. The former is implemented through incentives such as prices, energy trading, and even social interaction encouraging proactive consumer participation. In this method, the supplier can employ a high tariff if the system's reliability is compromised (Siano, 2014). Furthermore, some pricing schemes used are time of use (ToU), critical peak pricing (CPP), peak load pricing, real-time pricing (RTP), and variations thereof (Antunes et al., 2020). Regarding multi-level optimization, a strategy often used is day-ahead pricing, in which the consumer receives tariff information one day or some hours before (Carrasqueira et al., 2017). In the direct control method, the operator acts directly on the loads. Although direct control allows a better demand profile, it intervenes on users, making it unfeasible (Bragagnolo et al., 2020). Hence, a multi-level optimization is proposed in which the utility optimizes its pricing scheme to provide incentives for load shifting without direct intervention. Multilevel optimization is an NP-complex problem, where lower-level agents (users) can give multiple answers to the same proposition of the upper-level agent (supplier). Some authors propose the application of Karush-Kuhn-Tucker (KKT) conditions to convert the multilevel problem to a single-level problem and thus find the optimal solution. This transformation guarantees that the response of the set of users at the lower level is the optimal one for the supplier. As a disadvantage, it requires a considerable computational effort that only makes it applicable on a small scale (Antunes et al., 2020; Carrasqueira et al., 2017; Kovács, 2019). Moreover, cooperation between the distributor and the users is required (Antunes et al., 2020) and/or direct control over the users, with the need for computing concentrated on a single computer. However, in real life, the problems are often non-cooperative and users want to maintain their privacy (Antunes et al., 2020; Bragagnolo et al., 2020). For this reason, the transformation to a single level is not convenient, and the two levels are maintained. Additionally, these two levels allow taking advantage of the distributed computing resources on the users' side.

This article proposes a dual optimization method based on GA to optimize both the supplier objective function and the user cost. At the supplier level, two cases are proposed, and at the user level, the energy cost is minimized. In case 1, the demand profile is optimized based on grid energy conditions by modifying the pricing scheme; the supplier's goal is to obtain a flat demand, allowing better use of the infrastructure and generation resources. Case 1 is a novel approach and it follows technical conditions. In case 2, the supplier's objective is to maximize their profit by changing their pricing scheme, similarly to Meng and Zeng (2016). The users, who want to pay the least possible cost for the energy used, act on their shiftable loads. In both cases, a price scheme with time-variant pricing is proposed specifically, the day-ahead pricing will be used. Furthermore, several users with loads of different characteristics are modeled. Finally, the results achieved show the flattening of the demand curve.

The rest of the article is organized as follows: The related works are introduced in Section 2. Section 3 shows the theoretical framework and the user-supplier interaction model. To that end, the user consumption scheme is detailed, and the objective function for each level is discussed. The problem simulation and its results are shown in Section 4. Finally, the main conclusions are presented and future research is mentioned in Section 5.

## 2. Related works

On one side, the most recent demand management researches are based on indirect control. They are: 1) In Anvari-Moghaddam et al. (2015) a smart multi-objective residential home management system is performed to reduce consumption and improve user's comfort. 2) While Bertineti et al. (2019) use a greedy search algorithm to minimize the electrical cost and peak average ratio of a single user. 3) Essiet et al. (2019) propose an improved evolutionary differential algorithm that minimizes the electrical cost of a residential unit considering the user's comfort. 4) Whereas, Janocha et al. (2016) use a Mixed Integer Linear Programming (MILP) to manage the demand to minimize the cost. 5) Javaid et al. (2013) present a systematic review of various home energy management schemes. 6) Another approach was developed in Karami et al. (2014) where distributed energy resources are managed considering minimum operation cost. 7) Shaikh et al. (2018) develop an intelligent multi-objective system using an evolutionary genetic algorithm to optimize users' comfort and energy consumption. 8) Finally, Yang et al. (2015) develop a particle swarm optimization method (PSO) based on ToU, CPP, and demand response signals from the supplier to minimize cost while satisfying the constraints set by the user. In the direct control method, the operator acts directly on the loads. They are: 1) Batista and Batista (2018) propose an exact multi-objective methodology to optimize three different areas. 2) Gupta et al. (2016) develop a PSO applied to the demand of a residential area to minimize their peak consumption and their cost. 3) While Jung et al. (2020) perform the optimization of a microgrid under 4 different conditions and evaluate the effectiveness of each condition. (4)) In Li et al. (2015) two scheduling algorithms based on real-time price with renewable generation are proposed to control a large number of shiftable loads to minimize the electrical cost. 5) In Logenthiran et al. (2012) an evolutionary algorithm was proposed to minimize the cost of three different areas (residential, commercial, and industrial). 6) Nguyen and Le (2014) propose the optimization of a residential area to decrease the cost, considering the user comfort and they include the electric vehicle as a battery. 7) Rahate and Kinhekar (2017) use the PSO to optimize the demand of 200 users whereas the users define the priority of the shiftable loads. 8) Finally, Vidal et al. (2014) use an evolutionary algorithm and each user proposes the maximum load to be displaced.

On another side, multi-level optimization is a novel approach in DSM. 1) In Antunes et al. (2020), a literature review on multi-level optimization is presented. Most of the articles analyzed apply an economic standard on the supplier's side, i.e., the supplier wants to maximize its profit. Users can have one single objective, which is to minimize their cost or, additionally, maximize their comfort. The different techniques used to solve this problem are also mentioned, which cover the use of Karush-Kuhn-Tucker (KKT) conditions and traditional algorithms, as well as the use of heuristic algorithms. 2) Carrasqueira et al. (2017) propose a multilevel optimization to maximize supplier's profit and reduce electric bill, including user's comfort. To solve the optimization, they propose two heuristic algorithms and show that traditional algorithms do not provide an acceptable solution. 3) In Kovács (2019) a multilevel optimization is proposed, configured as a Stackelberg competition, the supplier wants to maximize its profit while the consumers reduce their costs. The problem is transformed into a single-level one employing a quadratic function, with quadratic constraints. In their literature review, most authors propose an economic approach for the supplier and they transform the two optimization levels into a single-level problem using the KKT conditions. In Besancon et al. (2020) a multilevel optimization is presented, configured as a Stackelberg competition with a time and level of use (TLOU) tariff scheme, where the supplier optimizes its profit and the consumers' reserve energy capacity. 4) In Meng and Zeng (2014), the game theory of Stackelberg (Leader-follower) is used. The supply uses a Genetic Algorithm (GA) to solve its optimal problem, while users use a linear programming method. 5) Finally, in Meng and Zeng (2016), a bi-level optimization is proposed, using a GA for the supplier and a linear programming method for the users. Both papers have the same goals: to minimize users' cost with load displacement and to maximize suppliers' profit by changing the pricing scheme. However, this situation does not guarantee the correct distribution of demand. Moreover, the us e of linear programming limits the modeling of different types of loads.

From the literature reviewed, researches using traditional algorithms optimize user's demand under a given pricing scheme through an indirect control approach. While heuristic algorithms were used for more complex loads or optimization of a large number of users. Furthermore, two approaches were used to optimize a large number of users, one requiring direct control over interruptible user loads or multi-level optimization. If multi-level optimization is transformed into a single-level optimization, the approach will be similar to the direct control. While maintaining both optimization levels mean an indirect control with supplier-users interaction. The interaction occurs because in each round if the supplier does not satisfy its objective, it will send new pricing schemes to the users who will propose their new strategy. As a summary of the analysis, it is concluded that: 1) The optimization of a single residential unit is an indirect control and it does not consider the risks of new peaks due to the concentration of loads in low-cost hours. 2) The direct control of a large number of users does not produce new peaks in the gird. But it is difficult to apply since it affects the users' privacy. 3) Multilevel optimization is generally transformed to a single level and it has an economic criterion. For these reasons, this article performs a multilevel optimization comparing a new technical approach with an economic one, which keeps the two levels of optimization to enable user-supplier interaction, uses the distributed computing resources, and does not affect the users' privacy.

## 3. DSM proposed method

This section describes the user model and the interaction with the supplier.

### 3.1. DSM and load Classification.

DSM consists of the automated control of the loads to operate the system and improve its sustainability (Vidal et al., 2014). Users' consumption patterns can be altered by changing their demand profile. In this sense, the DSM is an active approach that allows two major action categories: 1) reduce consumption; and 2) shift consumption (Belhaiza and Baroudi, 2015). Fig. 1 shows different actions that can be performed for the demand.

Appliances and equipment in residential units can be classified according to their consumption characteristics:

- Shiftable loads: these loads can be shifted from the moment that the peak demand occurs to any other desired moment or valley demand. Examples of these loads are washing machines, heating systems, etc.

- Interruptible loads: those that can be interrupted momentarily. Compensation may be required after the finalization of a demand response event. In this sense, the users may interrupt load use without affecting their life quality, considering that the operations will be completed within an appropriate period and produce financial benefits.
- Adjustable loads: are those in which the power demand is a continuous variable and can be controlled by the system, for example, an electric vehicle.
- Critical or non-interruptible loads: those that cannot be operated; for instance, a refrigerator that remains powered up all day. The operations of these applications are strictly dominated by comfort and necessity; therefore, their interruption threatens the user's life quality (Huang et al., 2016) (Zhu et al., 2015) (Bian et al., 2015).

According to this classification, Bragagnolo et al. (2020) prepared a table with loads found in a residential unit. The residential demand profile obtained in Celiz et al. (2018) for five users was used, in which 28 loads were assigned to each user. Three of them were proposed as shiftable loads with operation time range defined while all other loads are critical loads. Compared to Celiz et al. (2018), only the shiftable loads parameters are modified. Finally, a random assignment function was used to get ten users.

### 3.2. Definition and loads modeling

Table 1 shows three shiftable loads, defining type, operation time range, power, and duration.

The operation time range of shiftable loads is the variable constraint that handles the user's GA. Since the GA modifies the starting time of the shiftable load, this constraint fixes boundary values for this variable. To simplify the method, all users have the same restrictions in the hourly range of use.

### 3.3. Optimization

As the proposal is to establish the best supplier's pricing strategy as a response to the demand daily cost optimization, the optimization process of each user, as well as the supplier optimization process, are defined.

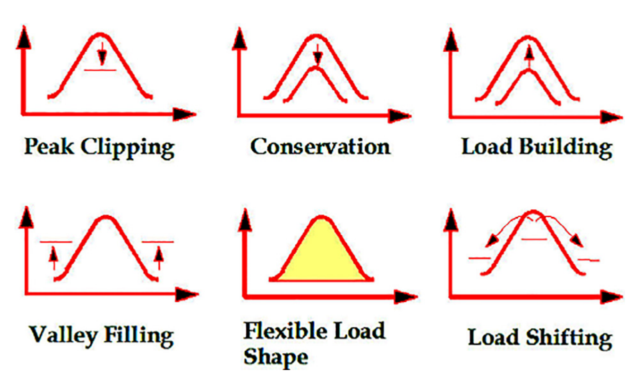


**Fig. 1.** Classic strategies used for DSM (Vidal et al., 2014).

**Table 1**
Shiftable Loads.

| Type | Operation time range [h] | Energy [Wh] | Duration [h] |
|---|---|---|---|
| Electric steam iron | 8:00 – 24:00 | 600 | 0,5 |
| Washing machines | All day | 182 | 1,5 |
| Dishwasher | All day | 1050 | 1 |

Each customer is considered to be equipped with a Smart Home Energy Management System (HEMS). The customer–supplier interactions are facilitated by a two-way communication infrastructure like the one shown in Fig. 2. In this process, the supplier sends several price signals to users in each round. Subsequently, the supplier gets the users' consumption strategy. If the supplier's goal is achieved, then the optimization process ends. This will be shown in Figs. 3 and 4 of section 4 which represent the user-supplier interaction algorithms.

A GA is used for each optimization level. The GA is a stochastic search method. In general, the evolutionary mechanism proceeds as follows: some individuals are selected to reproduce in a population, and those that are best adapted have more opportunities. During reproduction, new individuals in the population result from modifications and genetic exchange of the parents. Once the population is renewed, the process starts again (Ison et al., 2005). A heuristic algorithm is selected due to the flexibility to deal with different kinds of functions. Moreover, it can use discrete variables and it allows using functions of different nature. Finally, the GA algorithm is used because it has a random and probabilistic methodology and its computational cost to obtain a good solution.

### 3.3.1. User objective function

A user was modeled with 28 loads. The $\mathbf{A}_u$ matrix of binary states [0, 1] was used to indicate that the loads, of user *u*, are switched on or off. Intervals of 15 min were used as the measurement interval; then, 96 intervals represent a daily simulation time. $\mathbf{E}_u$ is the energy consumption vector of user *u*, and its element $e_i$ represents the energy consumed by load i.

$$X_u = A_u \cdot E_u \text{ with } X_u \in R^{96\times1} \wedge E_u \in R^{28x1} \tag{1}$$

By multiplying $\mathbf{A}_u$ by $\mathbf{E}_u$, (1) is obtained. The vector $\mathbf{X}_u$ represents the user's *u* strategy, where the element $(x_j)_u$ is the energy consumed by all loads switched on during the time interval *j*.

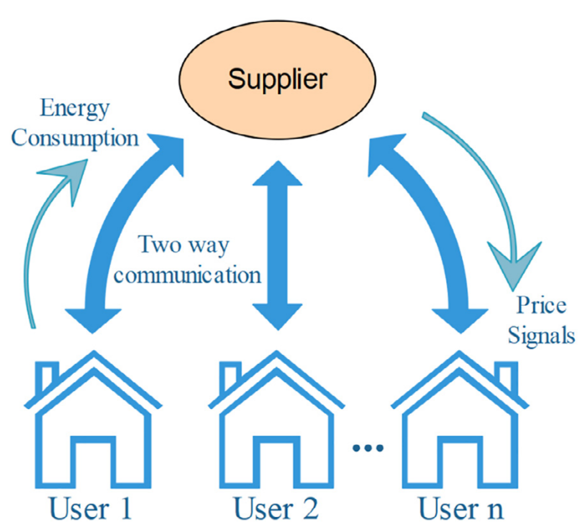


**Fig. 2.** Bilevel Model (Meng and Zeng, 2016).

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**Algorithm 1**: User demand profile optimization.

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**Input:** Matrix A of user n according to his preferences, vector E.
**Initialization:** Detection of new price signal P proposed by supplier.
**While** Operator sends new price signal
  Player n solves the function objective (2) using genetic algorithm.
  The new consumption strategy X (1) is obtained by the user and this is communicated to the supplier.
**End While**

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**Fig. 3.** Algorithm 1 for user optimization.

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**Algorithm 2:** Supplier optimization.

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**Input:** Expected demand profile of each user.
**Initialization:** Start GA an propose first population (prices vector) and informs each user.
**While** GA does not reach an optimum
  Propose a new population
  Send new pricing scheme to users
  Receive the news demand profile for each user.
  Perform the calculation of (4) or (7)
**End while**
**Output** Pricing scheme and total demand curve and graph of the results

---

**Fig. 4.** Algorithm 2 for supplier optimization.

The supplier suggests a pricing scheme **P** with a defined electrical price for each interval, where the element $p_j$ is the price proposes by the supplier during the time interval *j*

$$B_u = P^T X_u \text{ with } B \in R \wedge P \in R^{96x1} \tag{2}$$

The energy consumption cost of user u per day ($B_u$) is obtained by performing the dot product between $P^T$ and $\mathbf{X}_u$. Equation (2) is the electricity bill per day, and it is the objective function that each user seeks to minimize. This is done for each user through a HEMS. A GA was used to optimize (2) with the load constraints shown in Table 1. This differs from Meng and Zeng (2016) which uses a linear optimization algorithm on the user side.

### 3.3.2. Supplier objective function

Two supplier objective functions were modeled and their results were compared. Case 1: a novel technical criterion was proposed; therefore, the supplier modifies its rate system to flatten the demand curve. Case 2: an economic standard was chosen following Meng and Zeng (2016) in which the supplier's goal is to increase its profit by modifying the pricing scheme.

Given the technical criterion, the supplier has to compare -at each iteration- the length of each slot of demand made by all users with respect to the desired value in response to a day-ahead pricing scheme. Then, it chooses the selling price that produces a more flattened curve.

$$E_{PC} = \frac{\sum_{j=1}^{96}\sum_{u=1}^{n}(x_j)_u}{96} \text{ with } E_{PC} \in R \wedge (x_j)_u \in X_u \tag{3}$$

The desired value $E_{PC}$ is calculated as (3). It is a scalar that represents the energy consumption of all users per defined period through the day. $n$ is the number of users. Note that $\mathbf{X}_u$ is the strategy of the user $u$ to optimize their cost.

$$\Delta_E = \sum_{j=1}^{96}\left(\sum_{u=1}^{n}(x_j)_u - E_{PC}\right)^2 \text{ with } \Delta_E \in R \wedge (x_j)_u \in X_u \tag{4}$$

The demand flattening factor $\Delta_E$ (4) is based on (3). $\Delta_E$ is zero if the profile demand is flattened otherwise it will have a positive value. For this reason, (4) is the supplier's objective function when it considers technical issues. As the vector $\mathbf{X}_u$ changes when the price is modified, $\Delta_E$ changes.

$$g_j((x_j)_u, p_j) = b + \left(E_{pc} - \sum_{u=1}^{n}(x_j)_u\right)\cdot(p_j - 3) \geqslant 0 \text{ with } g_j \in G \tag{5}$$

Finally, the supplier has to optimize (4) subject to (5). This constraint function is included to get a better pricing scheme. If (5) does not exist, the price could not match the demand in some intervals; this could affect the convergence of the GA.

Equation (5) implies three conditions for it to be positive:

1- $p_j \geqslant 3y \sum_{u=1}^{n}(x_j)_u \geqslant E_{pc}$ the price is high if the demand exceeds the desired value $E_{pc}$.

2- $p_j < 3y \sum_{u=1}^{n}(x_j)_u < E_{pc}$ the price is low when there is lower than the desired value $E_{pc}$.

3- $p_j = 3$ this produces that the second term is zero.

3 ¢/kWh is chosen in the price because the price can vary between 1 and 5 ¢/kWh. Where 3 is the intermediate value. Furthermore, a constant term b is added to (5) where b = 1 because users could choose a different strategy for the same pricing scheme. Without this addition, procedures that satisfied a GA iteration may not satisfy the next one. After several simulations, the value of b = 1 was chosen considering that it gave a flexible band for cases where the second term of equation (5) was close to zero, and it was verified that the strategies that met this restriction were feasible in the following iteration.

$$C_j(L_j) = a_j L_j^2 + b_j L_j + c_j \tag{6}$$

For case 2, the supplier has to determine its profit - its revenue subtracting the energy cost. The cost function (6) proposed in Meng and Zeng (2016) was used. This indicates the cost of electricity supply per interval and $L_j$ represents the amount of power provided to all customers at interval $j$. This function is analogous to that used to determine the cost of a thermal generating machine. Where $a_j > 0$, $b_j \geq 0$ and $c_j \geq 0$ at each interval.

$$\text{Profit} = P^T \sum_{u=1}^{n} X_u - C^T \sum_{u=1}^{n} X_u \tag{7}$$

Equation (7) shows the retailer's profit that is calculated from (1), (2), and (6).

$$\text{Revenue} = P^T \sum_{u=1}^{n} X_u \leqslant R_{max} \tag{8}$$

The revenue constraint (8) was added in Meng and Zeng (2016) due to the market characteristics and to improve the acceptability of the retailer's pricing strategies.

As a result, the supplier optimizes (7) subject to (8). In (8), $R_{max}$ is the total revenue cap. If (8) does not exist, the prices will increase to a level that is unacceptable by customers, energy regulators, and/or the government (Meng and Zeng, 2016). Moreover, the upper bound of the problem space is limited to a maximum price $p_j \leq 5$. The lower bound is $p_j \geq 0$ due to the selling price is always positive. A negative value means that the supplier is purchasing energy. The lower limit differs from Meng and Zeng (2016) because it is not necessary to fix it with the supplier's electrical cost and it gives more flexibility in the pricing scheme.

*3.3.3. Existence of optimal solutions of the bilevel model*

First, consider the following bilevel model with one upper-level agent and "N" independent lower-level agent. Second, the supplier's objective is to reduce (4).

$$\min_{P,\, X_1,\ldots,\, X_n} F(P,\, X_1,\ldots,\, X_n)$$

Subject to: Subject to

$$\begin{aligned} &(X_1,\ldots,X_n) \in \operatorname{argmin}\left\{\sum_{u=1}^{n} B_u(P,\, X_u)\right\} \\ &G(P,\, X_1,\ldots,\, X_n) \leqslant 0 G(P,\, X_1,\ldots,\, X_n) \geqslant 0 \end{aligned} \tag{9}$$

Finally, (9) is expressed, and theorem 1 is established to prove that Case 1 converges toward a solution. In Meng and Zeng (2016) , the proof of case 2 is described.

**Theorem 1..** *Consider the model with one upper-level decision agent (supplier) and n independent lower-level decision agents (users) shown in (9). Since there is a price of the available energy lower than the peak energy -and because each user has shiftable loads-, they will move some of the peak energy to the available energy sector. Then both the supplier and the user achieve their respective goals so the solution converges.*

**Proof..** *For each decision variable $p_j$ (j = 1, …, 96) in the decision variable vector P at the upper-level problem, it only takes high values if the demand is high and as the user's objective is to reduce theirs bills and the displaceable energy is less or equal to the available energy, hence*:

1- For the same energy value, the cost of displacing the energy for the user is lower compared to the peak cost.

$$\int_{t_1}^{t_2} P_{t_1}^{t_2} E_{t_1}^{t_2}\, dt \leqslant \int_{t_n}^{t_m} P_{t_n}^{t_m} E_{t_n}^{t_m}\, dt \text{ with } P_{t_1}^{t_2} \leqslant P_{t_n}^{t_m} \tag{10}$$

The interval $[t_n, t_m]$ represents the peak time.

2- Each user has displaced energy and each one moves this to reduce their bill.

3- From 1 and 2 there is at least one solution in the considered bi-level optimization.

## 4. Experimental result

A detailed explanation of the implemented model and the required parameters are described in this section. The results obtained for both cases are compared against each other and a case without optimization that uses a flat pricing scheme.

*4.1. Simulation parameters.*

The data set, described in Table 1, was used for shiftable loads. Each appliance was switched on only once and an average energy value was calculated every 15 min, with no variation during the entire cycle of use.

$$p_n = p_{n+1} = p_{n+2} = p_{n+3} \text{ for } n = 1, 5, \ldots, 93 \tag{11}$$

The supplier proposed a pricing scheme with the limitation that the price may vary every 4 intervals (11). This avoids price fluctuations due to the inelasticity of a great portion of the demand.

Each user's demand profile was assigned according to a random function. The same seed was always used for this purpose, which allowed new simulations to get the same results. Besides, all users will have the same $\mathbf{E}_u$ consumption vector.

$$\text{Profiles} = \{A_1,\ A_2,\ A_3, A_4, A_5\} \tag{12}$$

$$\text{User}_u = \text{Profiles}(\text{Random}(1,5))\text{for}u = 1,\ \ldots\ ,\ 10 \tag{13}$$

The function is represented by (12) and (13) where A1, …, A5 corresponds to the profiles for 5 users and Random is the function with integers between 1 and 5.

For the cost of the energy provided to users by the retailer the cost function shown as (6) was used. The values of $a_j$, $b_j$ y $c_j$ were: $a_j = 0.04$ and $b_j = 0.25$ from 12 AM to 10 AM, $a_j = 0.055$ and $b_j = 0.5$ from 10 AM to 12 AM, $c_j = 0.5$ from 11 PM to 5 AM, $c_j = 0.75$ from 5 AM to 6 PM and $c_j = 1$ from 6 PM to 11 PM. These coefficients were developed following Meng and Zeng (2016) and the tariff scheme of EPEC [WWW Document], (2020).

Since there were two sequential optimization processes, two independent and coupled algorithms were proposed, one for the supplier and one for the user, following the structure represented by Fig. 3 and Fig. 4. In Fig. 4, the supplier can calculate (4) or (7) according to its goal.

If Algorithm 1 is not used, different pricing schemes will be sent to users, and they will be able to optimize their cost without the guarantee of avoiding new demand peaks. It arises from the analysis of Algorithm 2 that the supplier does not know either the loads that can be moved nor their operating times. It only knows the resultant expected demand profiles. The exact value will be measured afterward using smart meters. For these reasons, this method can be used for users that are concerned about their privacy.

### 4.2. Simulation results

Fig. 5 shows the demand profile of 10 users without optimization based on Celiz et al. (2018), with a flat pricing scheme. A constant price was decided throughout the day because this is the typical tariff scheme for residential users of Argentina's electricity distribution companies. The red bars represent the demand in kWh. The blue dashed line is the proposed price in ¢/kWh. The green line accounts for the calculated $E_{pc,}$ and the black dash-dot line is the cost of electricity supply.

Fig. 6 shows the demand profile obtained after the supplier optimization. In this case, the supplier's goal was to flatten the demand, according to (4) with the constraint (5). The price has similar behavior to the demand. It is usually less than 3 when the demand is less than the desired value and higher if the demand exceeds the desired value. Moreover, the displacement of demand from peak to off-peak hours can be appreciated.

The second case, in which the supplier's goal was to increase its profit, is shown in Fig. 7. The supplier optimized (7) with constraint (8). The price in Fig. 7 is usually higher than the price in Fig. 6 given the supplier's goal.

In both cases, the price of kWh could vary once every four consecutive elements of the vector, and the load was displaced for the

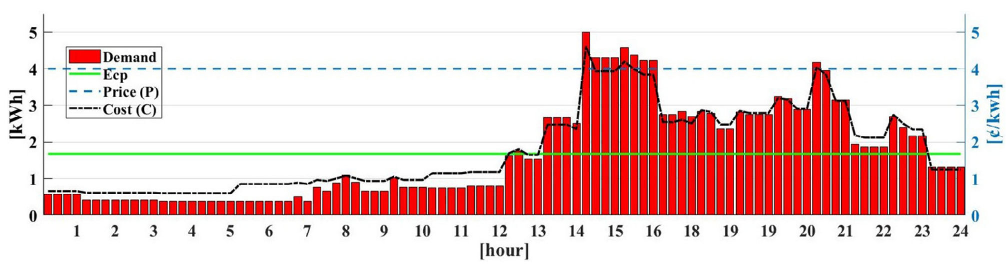


**Fig. 5.** Unscheduled demand profile based on (Celiz et al., 2018).

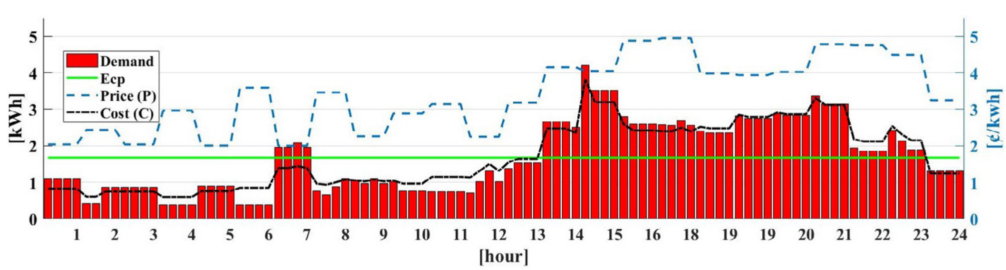


**Fig. 6.** Demand profile obtained after optimization with function objective (4) - Case 1.

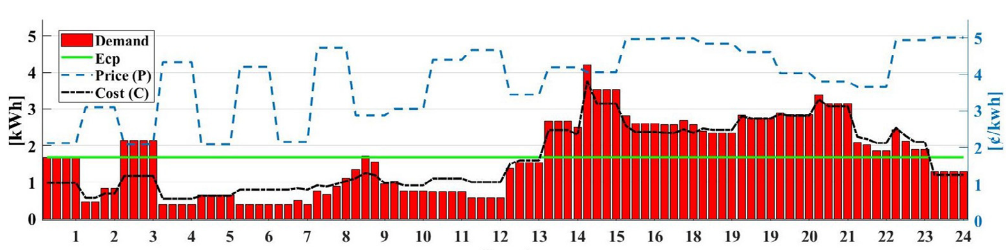


**Fig. 7.** Demand profile obtained after optimization with function objective (7) - Case 2.

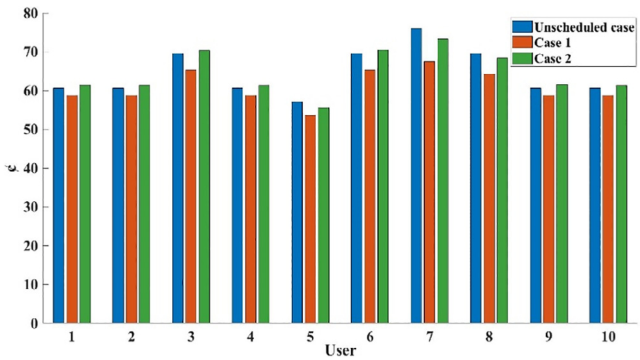


**Fig. 8.** Electricity bill per user.

**Table 2**
Simulation Results.

| Simulation | $\Delta_E$ | Average electricity bill [¢] | PAR |
|---|---|---|---|
| Unscheduled | 163.30 | 64.45 | 2.97 |
| Case 1 | 88.36 | 60.92 | 2.50 |
| Case 2 | 95.22 | 64.44 | 2.50 |

**Table 3**
Simulation Results.

| Simulation | Revenue [¢] | Cost [¢] | Profit [¢] |
|---|---|---|---|
| Unscheduled | 644.50 | 426.06 | 218.44 |
| Case 1 | 609.20 | 350.71 | 258.49 |
| **Case 2** | 644.44 | 351.43 | 293.01 |

peak hours to a place with less price. However, Fig. 6 shows more intervals with lower prices.

The electricity bill per user is observed in Fig. 8. Blue bars represent users without optimization, red bars users in case 1 (Fig. 6), and green bars users in Case 2 (Fig. 7). The cost for the user in Case 1 was always lower than the original situation whereas in Case 2, some users obtained a worse cost. This is the aim of the supplier's goal, to increase profits and the best situation has the same revenue as the unscheduled case. As a result, some users improved their costs at the expense of other users.

Table 2 and Table 3 summarize the comparison between the unscheduled users (Fig. 5) and the two bi-level optimization cases proposed (Fig. 6 and Fig. 7). Table 2 compares the flattening factor, the average electrical cost of ten users, and the peak to average ratio (PAR). Table 3 shows the revenue, cost, and profit in the three cases.

On the one hand, in Table 2 it is evident that in Case 1 the average cost of the ten users was less than the cost obtained before optimization. In this sense, the optimization result gives a $\Delta_{Eopt}$ = 88.36. This value was lower than the flattening factor of the unscheduled case. Although Case 2 presented the same peak to average ratio (PAR), the supplier had an upper flattening factor. Moreover, the users' average electric bill is similar to unscheduled simulation. In both cases, Table 2 shows a reduction of the PAR close to 16% (from 2.97 to 2.50).

On the other hand, Case 2 shows the best profit in Table 3. This increases up to 30% in comparison to the unscheduled case. Furthermore, both cases had a similar cost, lower than the unscheduled case. Case 1 had the lowest revenue. However, it had a better profit than the unscheduled simulation. This was a consequence of a better location of the loads and because all users improved their electric bill as shown in Fig. 8. Note that the $R_{max}$ for Case 2 was fixed as the revenue reached in the unscheduled case.

## 5. Conclusions

This paper shows that the technical criterion has advantages over the economic one. It could reduce the flattening factor and increase the supplier profit while all users reduce their electricity bills.

In the economic criterion, the utility achieves its highest profit and has a relatively good demand profile. However, some users suffer an increase in their bills. Therefore, it is not easy to encourage more users to participate in this market if they do not get any benefits from it.

Future works may analyze the trade-off between technical and economic criteria. On the user's side, comfort will be included in the objective function and other types of loads will be added to users. Finally, it will be complemented with a discussion about the cost function of the electricity supply, the convergence of the multilevel optimization process, and the type of solution found in the proposed technical approach.

## 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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