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Analysis of a Model for the Optimization of Energy Demand generated by End Users in Smart Grids

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Abstract. The increase in electricity demand, driven by economic, technological, and social growth, has posed significant challenges in terms of sustainability, costs, and dependence on external power grids. In Mexico, the residential sector has experienced sustained growth in electricity consumption, intensifying pressure on the grid and increasing reliance on fossil fuels. To address these issues, this study proposes an optimization model name as HOMENERGY-OPT to manage energy generation, storage, and consumption in residential smart grids (SGs). HOMENERGY-OPT employs a bottom-up engineering approach that incorporates household consumption behavior, device usage patterns, and sociodemographic characteristics. Its objectives include minimizing operational costs, reducing dependence on external sources, and maximizing the use of locally generated renewable energy. HOMENERGY-OPT was validated through experimental analysis under various photovoltaic panels (PV) configurations and energy storage capacities. Scenarios were evaluated to analyze the impact of these configurations on cost reduction and system efficiency. Results demonstrate that integrating optimization strategies into distributed generation systems improves operational efficiency and reduces energy costs for residential users. This research contributes to advancements in sustainable energy management by optimizing renewable resource use in SGs and provides a practical framework to address growing energy demand in the residential sector.
Keywords: optimization model, smart grid, energy demand.

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NOMENCLATURE

T	Ambient temperature (°C)	h_{lj}^{d}	Energy produced by PV l in the SG at time j and allocated to meet household energy demand
I	Irradiance (W/m²)	h_{lj}^{a}	Energy produced by the SGs PV at time j and allocated to storage
W	Wind speed (m/s)	h_{lj}^{a}	Energy produced by PV in the SG at time j and allocated to storage
B	Battery storage capacity (Ah)	h_{j}^{e}	Surplus energy produced by all PV in the SG at time j
E	System surplus energy at time j	h_{lj}^{e}	Surplus energy produced by PV l in the Smart Grid at time j
h	Amount of energy produced by the SGs PV	h'^{a}_{kj}	Accumulated energy, allocated from PV production to storage, for each battery k at time j
j	Time within the planning horizon	a_j	Amount of energy stored in all batteries of the SG at time j
i	Household device	a_{kj}	Amount of energy stored in battery k of the SG at time j
l	Photovoltaic Panel	a_j^d	Amount of energy stored in all batteries of the SG at time j and allocated to meet household energy demand

lm	PV capacity (kW)	a_{kj}^{a}	Energy allocated to storage in battery k of the SG time j
k	Number of batteries	$a_{k(j-1)}^{a}$	Energy allocated to storage in battery k of the SG at time j-1
c_j	Electric energy consumption at time j	a_{kj}^{d}	Energy stored in battery k of the SG and allocated to meet household energy demand, at time j
c_{ij}	Electric energy consumption of device i at time j	$a_{k(j-1)}^{d}$	Energy stored in battery k of the SG and allocated to meet household energy demand, utilized at time j-1
r_j	Energy supplied by CFE (kW/h)	a_j^{e}	Surplus energy from all batteries in the SG at time j
r'_j	Cumulative energy supplied by the external power grid at time j in watts (kW/h)	e_j	Energy price at time j
h_j^{d}	Energy produced by all Photovoltaic Panels in the Smart Grid and allocated to meet household energy demand at time j		

1 Introduction

The increase in electricity demand, driven by the growth of economic, technological, and social activities, has generated significant challenges in terms of sustainability, costs, and dependence on the external power grid. In Mexico, residential energy consumption has shown sustained growth in recent years. According to the Ministry of Energy (Secretaría de Energía, 2021), the net consumption of the National Electric System (SEN) increased by 3.5% in 2021 compared to the previous year, with the residential sector being one of the fastest-growing. This rise in demand has intensified pressure on the power grid, raising costs for end users and increasing dependence on fossil fuel-based energy sources, which in turn contributes to a larger carbon footprint.

To mitigate these effects and move toward more efficient energy management, the integration of renewable sources into smart grids has gained relevance. Among these sources, photovoltaic energy has proven to be a viable solution for decentralized electricity generation. However, several challenges remain in its implementation, such as the lack of optimal storage strategies, underutilization of generated energy, and the absence of optimization models that enable efficient energy consumption management in residential settings (Bragagnolo et al., 2020).

The optimization of energy demand and storage becomes crucial to reducing operational costs and improving system efficiency, allowing households to minimize their dependence on the external power grid and maximize self-consumption of renewable energy. In this context, the present study proposes an optimization model called HOMENERGY-OPT (Home Energy Optimization Model), designed to efficiently manage the generation, storage, and consumption of energy in residential smart grids. This model employs a bottom-up engineering-based modeling approach, which considers household energy consumption behavior, usage patterns of electrical devices, and the sociodemographic characteristics of homes. Through this methodology, the goal is to minimize the operational costs of the residential energy system by reducing the amount of energy purchased from the external grid and optimizing the use of internally generated energy (Gilardón, A., & Cristóbal, A., 2019).

To validate the effectiveness of HOMENERGY-OPT, an experimental analysis is conducted considering different configurations of energy storage and production. Scenarios are evaluated in which the number of batteries, storage capacity, number of solar panels, and energy production capacity of the panels vary, allowing an assessment of their impact on reducing the cost of energy consumed from the external energy operator, which in Mexico is the Federal Electricity Commission (CFE). According to previous studies, integrating optimization strategies in distributed generation has proven effective in improving operational efficiency and reducing energy costs in smart grids (Dufo-Lopez, R. & Bernal-Agustín, J., 2021). Thus, the proposal of this model not only contributes to better energy management at the residential level but also represents progress in designing strategies for the optimal use of renewable sources in smart electrical systems.

The remainder of this document is structured as follows: Section II presents the background and state of the art in energy optimization in residential smart grids. Section III describes in detail the proposed optimization model, including its mathematical formulation, constraints, and key decision variables. Section IV outlines the methodology used for experimentation, considering different energy storage and production scenarios. Section V presents the obtained results, while Section VI discusses the implications of the findings for optimizing residential energy consumption. Finally, Section VII provides the study's conclusions and its potential application in future research.

2 Background

To differentiate the approach of this study from the analyzed research, it is essential to highlight the key aspects that distinguish them in terms of scope, methodology, and application context.

While the reviewed studies analyze energy demand management, most address the issue from a broader perspective or with different objectives. First, several of these studies consider the integration of multiple renewable energy sources, such as solar, wind, and even hydroelectric power, focusing on optimizing hybrid systems in various environments (Dufo-Lopez, Rodolfo & Bernal-Agustín, José L., 2021). In contrast, this study focuses on optimizing residential energy management in a smart grid with photovoltaic generation and battery storage, ensuring a concrete and localized application.

Another distinguishing factor is the geographical scale of the studies. Most of the reviewed research is conducted in countries other than Mexico, and in some cases, the analysis is carried out at a macroeconomic level, considering national or regional energy management strategies (Ozdemir, G., 2024). Likewise, several studies are oriented toward rural and suburban environments, evaluating the feasibility of microgrids or distributed generation systems in communities with limited access to traditional energy infrastructure (Adewuyi, O. B., & Krishnamurthy, S., 2024). In contrast, this study is specifically designed for the reality of Mexico's electrical system, applied in an urban area such as Ciudad Madero, allowing for the capture of particular dynamics of residential energy consumption in this region.

Furthermore, while some of the reviewed studies focus on energy demand forecasting and prediction, employing artificial intelligence and machine learning techniques to estimate long-term trends (Ozdemir, G., 2024), this study adopts a practical and applied approach based on real household consumption patterns in Cd. Madero. Unlike predictive approaches, this optimization model considers specific data on consumer behavior, family composition, the availability of photovoltaic and storage infrastructure, and the region’s climatic conditions—factors that directly influence energy generation and use in a residential context.

Additionally, some reviewed studies propose distributed optimization techniques based on machine learning and demand response (Martínez, A., & Arévalo, P., 2025), while others analyze the efficiency of methods such as Black Widow optimization to enhance the performance of hybrid renewable energy systems (S. Divya, M., et al., 2024). In contrast, this study does not focus on advanced optimization algorithms or machine learning strategies but rather on the application of a deterministic energy optimization model aimed at maximizing efficiency and minimizing costs in a specific urban context.

2.1 Residential Energy Consumption

Studies have reported factors that impact residential energy consumption (Rastegar et al., 2016, Fujimoto et al., 2018, Pedrasa, Spooner, & MacGill, 2009, Beaudin et al., 2014). Electricity demand in the residential sector is influenced by the number and socioeconomic status of users, seasonality (Maqueda Zamora & Sánchez Viveros, 2011), and electricity prices (Cámara de Diputados, 2005). Higher income levels are associated with greater electricity consumption and demand (Maqueda Zamora & Sánchez Viveros, 2011). In the studies by (U.S. Department of Energy, 2009) and (Gers, 2017), it is considered that the number of devices in a residence impacts electricity consumption, with (Gers, 2017) concluding that understanding the implications of household appliances is essential to determine the savings or wear they generate. In the study by (Guacaneme et al., 2018), it was established that the following factors must be considered: 1) consumption habits to determine the nature of the loads, 2) voltage level, 3) number of appliances, and 4) energy consumed by each appliance to analyze the energy demand. In the work of (Laicāne et al., 2014), influencing factors in electricity consumption were classified into six categories: 1) Personal characteristics of the residents, including Age, Gender, Education level, Marital status, Household size and composition, 2) Socioeconomic factors of residents such as Household monthly income, Percentage of household expenditure on electricity consumption, Electricity price, Rebound effect, 3) Actions and presence of electrical appliances: Stock of electrical devices, Frequency of use, Percentage of energy-efficient devices, 4) Structural characteristics of the home, Type of home, Home size in m², Age of the home, Type of heating, and Temperature maintained during winter and summer. 5) Residents' behavior, including the effect of information, Knowledge/awareness/attitude toward electricity consumption. 6) Other factors such as Geographic location, zone, and Climate characteristics.

The increase in energy demand in Mexico and the need to optimize residential consumption take place within the framework of national energy policies, including the Energy Transition Law (LTE), the Energy Transition and Sustainable Energy Use Fund (FOTEASE), and the National Commission for the Efficient Use of Energy (CONUEE). These policies aim to increase the share

of renewables through clean energy generation, reduce greenhouse gas emissions, and establish a regulatory framework for distributed generation to promote the adoption of renewable energy at the residential level.
In this context, HOMENERGY-OPT seeks to address the inefficient management of energy demand in residential settings by tackling external grid dependency, the underutilization of generated solar energy, and the lack of optimal storage strategies. HOMENERGY-OPT allows residential users to benefit from cost reductions and increased efficiency, contributing to the achievement of national clean energy and sustainability goals.

2.2 Factors Impacting Residential Electricity Consumption in Mexico

In the work of Macías et al. (2018), it was considered that factors such as building type, total income, the area in square meters of air conditioning, the number of residents, temperature, and the season of the year directly impact electricity consumption in Mexico. The CONUEE (National Commission for the Efficient Use of Energy) (2020) established that key factors to consider include the level of equipment, equipment efficiency, number of occupants, usage patterns and habits of the appliances, and the local climate where the residence is located. According to the research by Morales Ramírez, et al (2021), factors such as family size, age, the presence of children, education level, economic situation, type of house, and household appliances were considered, highlighting their significant impact on energy consumption.

In summary, while the reviewed studies provide valuable analyses of energy demand management across different scales and conditions, this study stands out for its localized and applied approach. It considers a specific case study in an urban area of Mexico, incorporating real consumption patterns and specific environmental conditions. This ensures that the proposed model is not only theoretically robust but also replicable and adaptable to similar realities within the country.

3 Objective

To propose and evaluate an energy optimization model applied to residential environments in smart grids, considering real consumption patterns, local climatic conditions, and the electrical system configuration of Ciudad Madero. The objective is to minimize operational costs, reduce dependence on the external power grid, and maximize the utilization of photovoltaic energy stored in batteries.

4 Methodology

There are two approaches to studying energy consumption: top-down and bottom-up. Top-down methods aim to understand consumer behavior by analyzing variations in the supply and prices of electricity. Their names refer to the hierarchical position of the data inputs. The top-down method does not distinguish the individual final use of energy consumption in the residential sector, but rather considers variables such as macroeconomic indicators (Gross Domestic Product (GDP), employment rates, and price indices), climate conditions, construction, and other factors. It is further classified into econometric and technological methods. A disadvantage of these methods is their dependence on historical energy consumption records to estimate increases and variations in the variables. The bottom-up method, on the other hand, considers the energy consumption of end-users, whether individual or in a group of households, as well as representative characteristics of the region. This approach is divided into two methods: statistical and engineering. The statistical method uses data on the energy billing of clients with the energy supplier, housing characteristics, and the behavior of the occupants in each residential unit. The engineering method computes the energy consumption of end-users based on their characteristics. This is the only method that can be completed without requiring historical energy consumption data; instead, it can be modeled using simple characteristics and takes into account the behavior of the occupants within the household. Therefore, the engineering bottom-up method allows for the direct calculation of energy consumption based on the end uses of energy by each user in one or more residences (Swan & Ugursal, 2009).

The proposed HOMENERGY-OPT employs a bottom-up engineering modeling approach, which means it starts with a detailed analysis of energy consumption at the device and user level within the household to structure an efficient energy management strategy. To achieve this, real energy consumption data is considered, including usage habits of electrical devices, the hourly distribution of consumption, and the household's sociodemographic characteristics. This enables an accurate characterization of residential energy demand. The parameters considered for HOMENERGY-OPT consist of a set of physical, operational, and economic factors that influence household energy management, classified into four categories: 1) Energy Consumption – monitored electrical devices, user usage patterns, and the total household energy load, 2) Energy Generation – number of photovoltaic panels, photovoltaic production capacity, and climatic condition, 3) Energy Storage – number of batteries and battery storage capacity, 4) Economic and Power Grid Factors – electricity tariff, energy acquired from the external power grid (CFE), and the total system operating cost.

5 HOMENERGY-OPT Development

HOMENERGY-OPT is based on a detailed analysis of residential energy consumption in a smart grid, aiming to minimize operational costs, reduce dependence on the external power grid, and maximize the utilization of photovoltaic energy stored in batteries.

The current optimization model consists of four objectives: 1) $f(r) = \sum_{j=1}^{m} e_j r_j$ it is related to the cost of energy, el 2) $g(E) = \sum_{j=1}^{m} E_j$, $h(E)$ it focuses on minimizing the total excess energy, el 3) $h(E) = -\sum_{j=1}^{m} e'_j E_j$ it aims to maximize the excess energy, and 4) $i(r, E) = \sum_{j=1}^{m} e_j r_j - \sum_{j=1}^{m} e'_j E_j$ it seeks to minimize the cost of energy from the external service provider and the cost associated with excess energy.

$$min\ \mathrm{F(r)} = \left\{ f(r) = \sum_{j=1}^{m} e_j r_j , g(E) = \sum_{j=1}^{m} E_j , h(E) = -\sum_{j=1}^{m} e'_j E_j , i(r,E) = \sum_{j=1}^{m} e_j r_j - \sum_{j=1}^{m} e'_j E_j \right\} \tag{1}$$

where,

$h_{lj} = h(T(j), I(j), W(j))$, It is calculated based on the work of (Gilardón, A. & Cristóbal, A., 2019) using temperature (*T*), irradiance (*I*), and wind (*W*).

The objective function is crucial for the model, as it guides all decisions within the model. This function aims to: 1) balance consumption and production, ensuring that energy production is sufficient to meet demand without incurring excessive costs; 2) maximize efficiency by fully utilizing available renewable energy sources and properly managing storage (batteries); and 3) minimize costs by reducing expenditure associated with the purchase of external energy and maximizing the use of energy generated internally.

5.1. Breakdown of HOMENERGY-OPT

Equation (2) calculates the total cost of the energy supplied by the external power grid (CFE) in each period j by multiplying the energy price by the amount of energy consumed. The objective is to minimize this cost.

$$f(r) = \sum_{j=1}^{m} e_j r_j \tag{2}$$

Equation (3) aims to maximize the total energy surplus produced by the system in each period. An energy surplus indicates that more energy is generated than consumed, which is desirable to ensure the system's sustainability.

$$g(E) = \sum_{j=1}^{m} E_j, \tag{3}$$

Equation (4) accounts for the costs or revenues associated with the unused surplus energy. If the surplus energy holds value—whether through sale or storage as savings—it can reduce the total cost by introducing a negative income term into the objective function.

$$h(E) = -\sum_{j=1}^{m} e'_j E_j \tag{4}$$

Equation (5) seeks to balance the total cost of consumed energy with the revenues or savings generated by the energy surplus. The objective is to maximize this balance, ensuring that costs are offset by the benefits derived from efficient resource management, thereby minimizing the expenses incurred by the external service operator (CFE).

$$i(r, E) = \sum_{j=1}^{m} e_j r_j - \sum_{j=1}^{m} e'_j E_j \tag{5}$$

Once the objective function was defined, eleven constraints were developed for the HOMENERGY-OPT. These constraints were established as conditions that must be met to ensure that the HOMENERGY-OPT operates optimally and realistically. They are described as follows:

Constraint 1 ensures that energy production is sufficient to meet demand. That is, the sum of the energy generated by photovoltaic panels, the energy stored in batteries, and the energy supplied by the external grid (CFE) must be equal to the total household energy consumption (Eq. 6).

$$h_j^d + a_j^d + r_j = \sum_{i=1}^{n} c_{ij} x_{ij} \tag{6}$$

Constraint 2 verifies that all the energy produced by the photovoltaic panels is entirely distributed among demand, storage, and surplus (Eq. 7).

$$h_{lj}^d + h_{lj}^a + h_{lj}^e = h_{lj} \tag{7}$$

Constraint 3 states that, at each time period *j*, the energy produced by the photovoltaic panels allocated to meet demand must match the total energy generated by all photovoltaic panels (Eq. 8).

$$h_j^d - \left(\sum_{l=1}^{L} h_{lj}^d \right) = 0 \tag{8}$$

Constraint 4 ensures that the energy produced by the photovoltaic panels and allocated for storage must match the total energy generated by all photovoltaic panels that has been designated for storage at each time period *j* (Eq. 9).

$$h_j^a - \left(\sum_{l=1}^{L} h_{lj}^a \right) = 0 \tag{9}$$

Constraint 5 establishes that the energy generated by the photovoltaic panels for storage must match the sum of the energy allocated to be stored in each battery *k* at each time period *j* (Eq. 10).

$$h_j^a - \left(\sum_{k=1}^{K} {h'}_{kj}^a \right) = 0 \tag{10}$$

Constraint 6 states that the stored energy allocated to meet household demand must be equal to the sum of all stored energy designated for demand coverage across all batteries *k* at time *j* (Eq. 11).

$$a_j^d - \left(\sum_{k=1}^{K} a_{kj}^d \right) = 0 \tag{11}$$

Constraint 7 establishes that the storage capacity of each battery *k* must not be exceeded at any time *j* (Eq. 12).

$$a_{kj}^a \leq B \tag{12}$$

Constraint 8 ensures that the energy allocated for storage is not less than the energy extracted from the batteries to meet demand. In other words, it guarantees that no more energy is withdrawn than has been previously stored in the batteries. This is crucial to avoid an energy supply deficit and to maintain the integrity of the storage system (Eq. 13).

$$a_{kj}^{a} - a_{kj}^{d} \geq 0 \tag{13}$$

Constraint 9 ensures that the state of charge of each battery k in period $j+1$ is correctly calculated based on the state of charge in period j, considering both stored energy and the energy extracted to meet demand (Eq. 14).

$$a_{kj+1}^{a} - \left(a_{kj}^{a} - a_{kj}^{d}\right) - h'^{a}_{kj} = 0 \tag{14}$$

Constraint 10 establishes that the amount of energy stored in the batteries at the beginning of the period must be equal to the known initial charge of each battery. This data is fundamental for initiating the model with a realistic and accurate system state, ensuring that subsequent simulations correctly reflect the initial conditions of the energy system (Eq. 15).

$$a_{k0}^{a} = a_{k}^{ini} \tag{15}$$

Constraint 11 ensures that the total energy surplus in each period j is equal to the sum of the surplus energy produced by all solar panels. This guarantees that all generated energy that is not used for immediate consumption or storage is properly accounted for. The efficient management of surplus energy is essential for optimizing resource utilization and maximizing the economic benefits of the system (Eq. 16).

$$E_j - \left(\sum_{l=1}^{L} h_{lj}^{e}\right) = 0 \tag{16}$$

Together, these constraints form a cohesive system that enables the HOMENERGY-OPT to simulate realistic scenarios within a smart grid. By ensuring that all aspects of energy flow—from generation to consumption and storage—are considered, this approach facilitates efficient energy resource management. Moreover, it provides a solid foundation for implementing optimization practices in the energy sector. The proper implementation and adherence to these constraints will allow the proposed objectives to be achieved in terms of sustainability and economic efficiency within the household.

6 Experimentation

To conduct the experimentation, an experimental design was applied. This design is based on a quantitative and observational approach, relying on the collection of real energy consumption data from a representative household in Ciudad Madero, Mexico. To ensure the accuracy of the optimization model, a real-time energy monitoring methodology was implemented, recording the use of electrical devices, consumption patterns, and residents' energy behavior continuously for seven days, 24 hours a day, resulting in a planning horizon of 168 hours. During the study period, the individual usage of each appliance (usage pattern) and electrical device (22 devices within the household) was documented, determining their operating time and the amount of energy consumed in each time interval (W/h). Additionally, the number of batteries, the number of solar panels, the maximum capacity of each battery, and the energy production of each photovoltaic panel (W/h) were recorded to evaluate their impact on photovoltaic generation and energy demand. Table 1 provides detailed information on each parameter considered.

Table 1. Parameters considered for the experimentation.

<table>
<tr><td>List of household devices (i):</td><td colspan="4">Refrigerator, Television (TV) (2), Light bulbs (6), Air conditioner (AC) (4), Fan (4), Electric stove, Laptop, Modem, Blender, Washing machine.</td></tr>
<tr><td>Planning horizon:</td><td colspan="4">168 hours (1 week)</td></tr>
<tr><td>Number of batteries (k):</td><td colspan="4">1, 10, 20</td></tr>
<tr><td>Number of photovoltaic panels (l):</td><td colspan="4">4, 8, 16</td></tr>
<tr><td>Maximum capacity of each battery (Ah):</td><td colspan="4">1000, 3000, 5000</td></tr>
<tr><td>Energy consumption of each device (W/h):</td><td>Refrigerator
TV
Light bulbs
AC
Fan</td><td>1600
260 ea
10 ea
1900 ea
320 ea</td><td>Electric stove
Laptop
Modem
Blender
Washing machine</td><td>1500
200
18
600
1500</td></tr>
<tr><td>Energy production per PV (kW):</td><td colspan="4">200, 330, 600</td></tr>
<tr><td>End-user usage pattern:</td><td colspan="4">A family of four members (Father (F), Mother (M), Son (S), and Daugter (D)).</td></tr>
</table>

Figure 1 illustrates the time periods during which each user is at home or away, as well as their sleep schedule. This latter information supports the modeling of air conditioning usage, as users only turn on the air conditioning while sleeping.

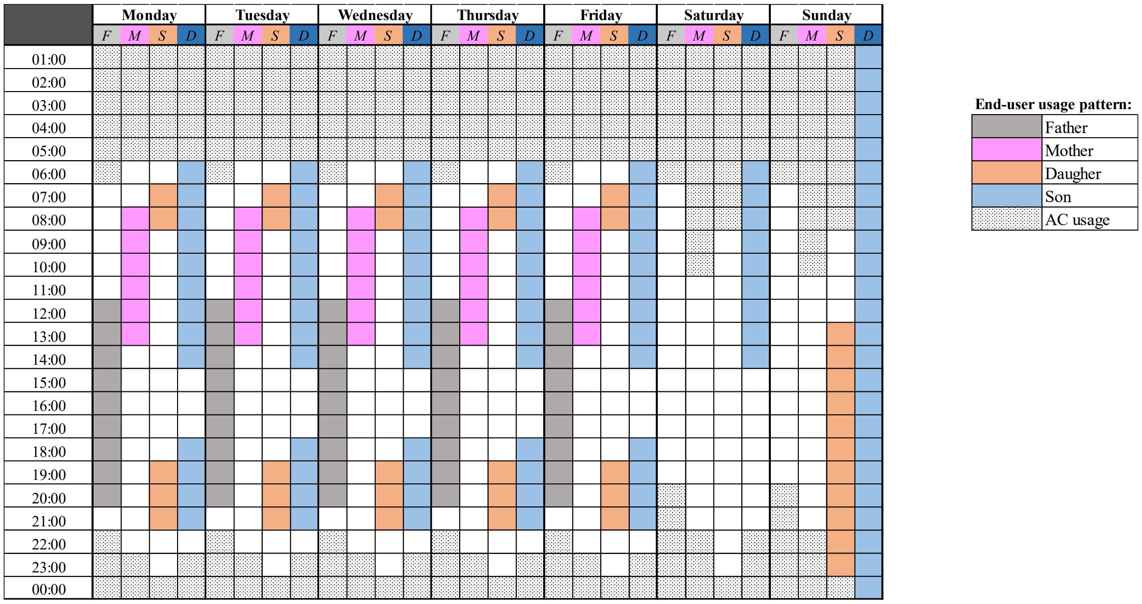
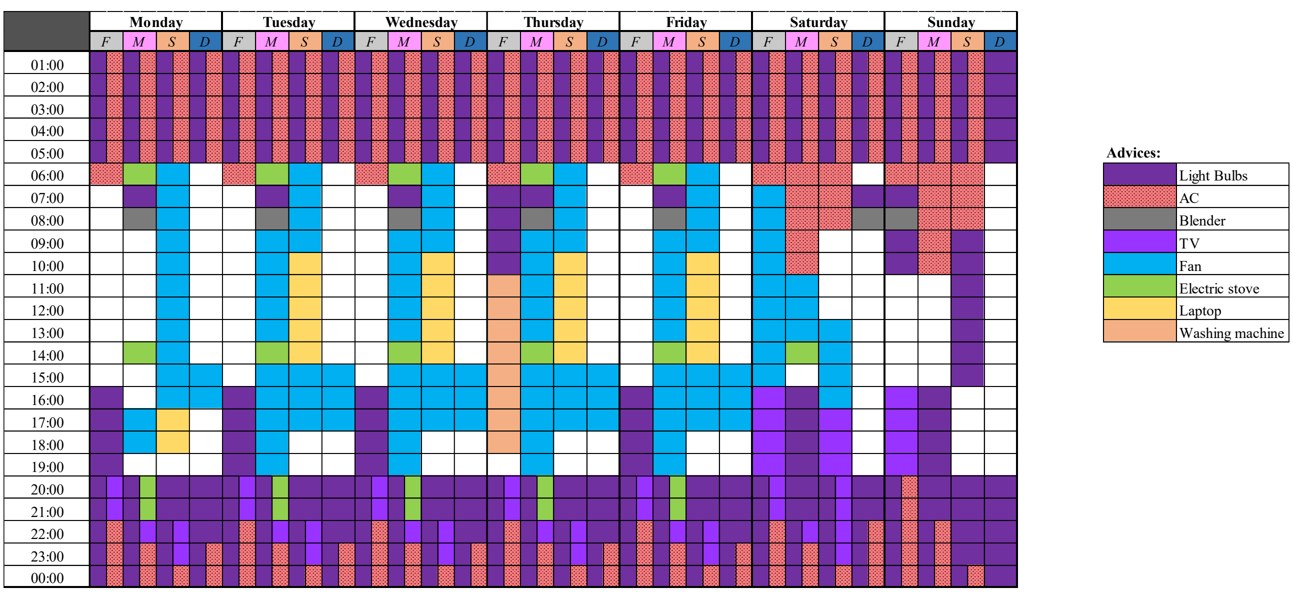


Figure 1. Modeling of each end user's stay within the residence.

Based on the modeling of each user's presence within the household, the usage of each device by each user was modeled over the proposed planning horizon. This consumption pattern per device is detailed in Figure 2, which represents the 22 devices considered in this residential case study, including a refrigerator, televisions (2), light bulbs (6), air conditioners (4), fans (4), an electric stove, a laptop, a modem, a blender, and a washing machine.



Note: *The energy consumption of the refrigerator and the modem was considered as continuously plugged in, meaning they remain connected to the power supply 24 hours a day.*

Figure 2. Energy usage pattern of each device by each user within the household.

Based on the device usage pattern and the electrical consumption of each device, the total household energy consumption within the considered planning horizon amounts to 980,464 kWh. Regarding the energy consumption cost, the Federal Electricity Commission (CFE) applies different tariff schemes (industrial and residential), with the residential tariff scheme being of interest. Within this scheme, specific domestic incentive tariffs are available (1, 1A, 1B, 1C, 1D, 1E, 1F) as well as high-consumption domestic tariffs (DAC). For this case study, the 1C tariff for 2024 was considered, which applies to residential service in locations with a minimum average summer temperature of 30°C. Since March marks the beginning of summer in the studied locality, the corresponding December tariff was consulted. For the non-summer season, the basic consumption rate (*Ba*) is set at $1.059 per kWh for the first 75 kWh, the intermediate consumption rate (*Inter*) is $1.285 per kWh for the next 100 kWh, and the excess consumption rate (*Exc.*) is $3.763 per kWh for any additional consumption beyond these thresholds.

It is acknowledged that the accuracy and applicability of the model would be enhanced by incorporating real data on residential electricity tariffs in Mexico, which are expressed in Mexican pesos (MXN).

	k	*l*	*B*	*lm*	r^d	*Difference*
1	20	16	3000	600	280,538	699,926
2	20	16	5000	600	280,538	699,926
3	10	16	5000	600	329,248	651,216
4	10	16	3000	600	454,258	526,206
5	20	16	1000	600	524,258	456,206
6	10	16	3000	330	579,364	401,100
7	10	16	5000	330	579,364	401,100
8	20	16	1000	330	579,364	401,100
9	20	16	3000	330	579,364	401,100
10	20	16	5000	330	579,364	401,100
11	10	16	1000	600	594,258	386,206
12	10	16	1000	330	606,184	374,280
13	20	8	5000	600	627,664	352,800
14	10	8	1000	600	627,664	352,800
15	10	8	3000	600	627,664	352,800
16	10	8	5000	600	627,664	352,800
17	20	8	1000	600	627,664	352,800
18	20	8	3000	600	627,664	352,800
19	1	16	5000	600	629,258	351,206
20	1	16	3000	600	643,258	337,206
21	1	16	5000	330	650,312	330,152
22	1	16	3000	330	651,776	328,688
23	1	8	5000	600	652,712	327,752
24	1	16	1000	600	657,258	323,206
25	1	8	3000	600	659,828	320,636
26	1	16	1000	330	664,096	316,368
27	1	8	1000	600	672,028	308,436
28	10	16	1000	200	734,064	246,400
29	10	16	3000	200	734,064	246,400
30	10	16	5000	200	734,064	246,400
31	20	16	1000	200	734,064	246,400
32	20	16	3000	200	734,064	246,400
33	20	16	5000	200	734,064	246,400
34	1	16	1000	200	734,568	245,896
35	1	16	3000	200	734,568	245,896
36	1	16	5000	200	734,568	245,896
37	1	8	1000	330	782,644	197,820
38	1	8	3000	330	782,644	197,820
39	1	8	5000	330	782,644	197,820
40	10	8	1000	330	782,644	197,820
41	10	8	3000	330	782,644	197,820
42	10	8	5000	330	782,644	197,820
43	20	8	1000	330	782,644	197,820
44	20	8	3000	330	782,644	197,820
45	20	8	5000	330	782,644	197,820
46	1	4	1000	600	812,464	168,000
47	1	4	3000	600	812,464	168,000
48	1	4	5000	600	812,464	168,000
49	10	4	1000	600	812,464	168,000
50	10	4	3000	600	812,464	168,000
51	10	4	5000	600	812,464	168,000
52	20	4	1000	600	812,464	168,000
53	20	4	3000	600	812,464	168,000
54	20	4	5000	600	812,464	168,000
55	1	8	1000	200	857,264	123,200
56	1	8	3000	200	857,264	123,200
57	1	8	5000	200	857,264	123,200
58	10	8	1000	200	857,264	123,200
59	10	8	3000	200	857,264	123,200
60	10	8	5000	200	857,264	123,200
61	20	8	1000	200	857,264	123,200
62	20	8	3000	200	857,264	123,200
63	20	8	5000	200	857,264	123,200
64	1	4	1000	330	884,284	96,180
65	1	4	3000	330	884,284	96,180
66	1	4	5000	330	884,284	96,180
67	10	4	1000	330	884,284	96,180
68	10	4	3000	330	884,284	96,180
69	10	4	5000	330	884,284	96,180
70	20	4	1000	330	884,284	96,180
71	20	4	3000	330	884,284	96,180
72	20	4	5000	330	884,284	96,180
73	1	4	1000	200	918,864	61,600
74	1	4	3000	200	918,864	61,600
75	1	4	5000	200	918,864	61,600
76	10	4	1000	200	918,864	61,600
77	10	4	3000	200	918,864	61,600
78	10	4	5000	200	918,864	61,600
79	20	4	1000	200	918,864	61,600
80	20	4	3000	200	918,864	61,600
81	20	4	5000	200	918,864	61,600

Figure 3. Results of the optimization model application in the proposed experimental design.

For the experimentation, multiple simulation scenarios were established, varying key parameters of the energy system, such as:
- Number of solar panels (l): 4, 8, and 16 units.
- Photovoltaic generation capacity (lm): 200, 330, and 600 kW.
- Number of batteries (k): 1, 10, and 20 units.
- Battery storage capacity (B): 1000, 3000, and 5000 Ah.

Each scenario was designed to analyze the relationship between photovoltaic generation, energy storage in batteries, and household electricity consumption, allowing the evaluation of how system optimization reduces dependence on the external power grid and minimizes operational costs.

The applied experimental design enabled the validation of the proposed model's efficiency under real consumption conditions, considering the available infrastructure and the climatic conditions of Ciudad Madero. The use of real data obtained through fieldwork distinguishes this study from other theoretical models or those based on general consumption estimates. The direct collection of energy information from a household allowed the development of a highly accurate model, tailored to the residents' consumption patterns and the local solar generation conditions in Ciudad Madero. This approach enables a more realistic assessment of the impact of energy optimization on cost reduction and system efficiency within a smart grid. It is important to note that ideal conditions were considered for the photovoltaic panel production capacity value.

	k	*l*	*B*	*lm*	*Reduction*
1	20	16	3000	600	**71.39%**
2	20	16	5000	600	**71.39%**
3	10	16	5000	600	**66.42%**
4	10	16	3000	600	**53.67%**
5	20	16	1000	600	**46.53%**
6	10	16	3000	330	**40.91%**
7	10	16	5000	330	**40.91%**
8	20	16	1000	330	**40.91%**
9	20	16	3000	330	**40.91%**
10	20	16	5000	330	**40.91%**
11	10	16	1000	600	**39.39%**
12	10	16	1000	330	**38.17%**
13	20	8	5000	600	**35.98%**
14	10	8	1000	600	**35.98%**
15	10	8	3000	600	**35.98%**
16	10	8	5000	600	**35.98%**
17	20	8	1000	600	**35.98%**
18	20	8	3000	600	**35.98%**
19	1	16	5000	600	**35.82%**
20	1	16	3000	600	**34.39%**
21	1	16	5000	330	**33.67%**
22	1	16	3000	330	**33.52%**
23	1	8	5000	600	**33.43%**
24	1	16	1000	600	**32.96%**
25	1	8	3000	600	**32.70%**
26	1	16	1000	330	**32.27%**
27	1	8	1000	600	**31.46%**
28	10	16	1000	200	**25.13%**
29	10	16	3000	200	**25.13%**
30	10	16	5000	200	**25.13%**
31	20	16	1000	200	**25.13%**
32	20	16	3000	200	**25.13%**
33	20	16	5000	200	**25.13%**
34	1	16	1000	200	**25.08%**
35	1	16	3000	200	**25.08%**
36	1	16	5000	200	**25.08%**
37	1	8	1000	330	**20.18%**
38	1	8	3000	330	**20.18%**
39	1	8	5000	330	**20.18%**
40	10	8	1000	330	**20.18%**
41	10	8	3000	330	**20.18%**
42	10	8	5000	330	**20.18%**
43	20	8	1000	330	**20.18%**
44	20	8	3000	330	**20.18%**
45	20	8	5000	330	**20.18%**
46	1	4	1000	600	**17.13%**
47	1	4	3000	600	**17.13%**
48	1	4	5000	600	**17.13%**
49	10	4	1000	600	**17.13%**
50	10	4	3000	600	**17.13%**
51	10	4	5000	600	**17.13%**
52	20	4	1000	600	**17.13%**
53	20	4	3000	600	**17.13%**
54	20	4	5000	600	**17.13%**
55	1	8	1000	200	**12.57%**
56	1	8	3000	200	**12.57%**
57	1	8	5000	200	**12.57%**
58	10	8	1000	200	**12.57%**
59	10	8	3000	200	**12.57%**
60	10	8	5000	200	**12.57%**
61	20	8	1000	200	**12.57%**
62	20	8	3000	200	**12.57%**
63	20	8	5000	200	**12.57%**
64	1	4	1000	330	**9.81%**
65	1	4	3000	330	**9.81%**
66	1	4	5000	330	**9.81%**
67	10	4	1000	330	**9.81%**
68	10	4	3000	330	**9.81%**
69	10	4	5000	330	**9.81%**
70	20	4	1000	330	**9.81%**
71	20	4	3000	330	**9.81%**
72	20	4	5000	330	**9.81%**
73	1	4	1000	200	**6.28%**
74	1	4	3000	200	**6.28%**
75	1	4	5000	200	**6.28%**
76	10	4	1000	200	**6.28%**
77	10	4	3000	200	**6.28%**
78	10	4	5000	200	**6.28%**
79	20	4	1000	200	**6.28%**
80	20	4	3000	200	**6.28%**
81	20	4	5000	200	**6.28%**

Figure 4. Percentage of reduction in energy supplied by the power grid operator after applying the optimization model in the experimental design.

7 Results

The energy consumption of users in a SG within the household during the considered period totals 980,464 kWh, which would result in a payment of $3,053.04 to the external energy operator (CFE). However, upon applying the optimization model with the proposed values in the experimental design for *k = 1, 10, 20; l = 4, 8, 16; B = 1000, 3000, 5000*; and *lm = 200, 330, 600*, a reduction in the user's dependence on energy supplied by CFE (71.39%) was observed. This was coupled with the increased utilization of energy provided by the photovoltaic (PV) systems (maximizing benefits through the optimization model) and a significant reduction in the payment for electricity service to the external energy operator, dropping from $3,053.04 to $419.21, representing an 86.3% reduction in the electricity service payment.

Figure 5 shows the relationship between electricity cost, the number of batteries, and their interaction with the variables l, B, and *lm.* The number of batteries considered (*k*) was 1, 10, and 20. For the case with a single battery, a decrease in energy cost was observed. The highest percentage reduction in this case was 43.3%, while the lowest percentage reduction in energy cost was 7.6%. It is important to emphasize that the larger the battery storage capacity, the greater the impact on cost reduction and energy utilization. For instance, in combination 27 (*k=1, B=5000, l=4, lm=200*), a 38% reduction was achieved. In contrast, combination 19 (*k=1, B=5000, l=16, lm=600*) achieved a 43.3% reduction, equivalent to a payment of $1,731.45. This reduction was due to both the increased PV capacity and the higher energy production of the PV systems. This indicates that as energy production increases, higher storage capacity and more batteries are needed to store the produced energy. This observation is further validated in combination 2 (*k=20, B=5000, l=16, lm=600*), where an 86.3% reduction was achieved, while combination 3 (*k=10, B=5000, l=16, lm=600*) resulted in an 80.3% reduction.

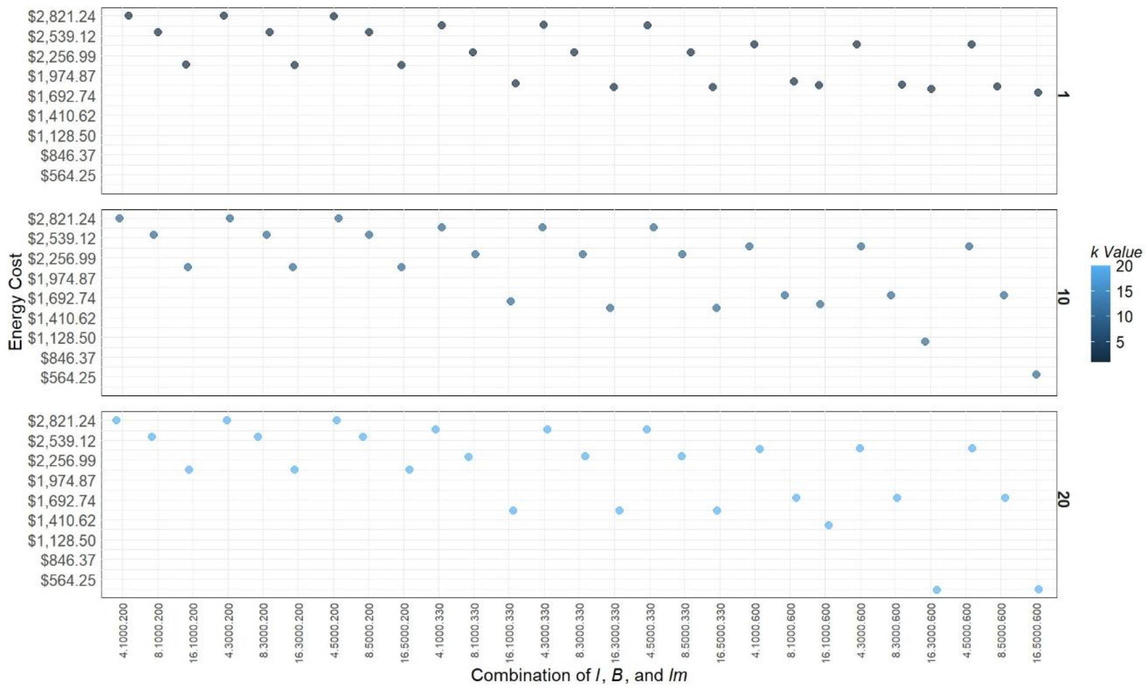


Figure 5. Relationship between energy cost and different combinations of variables *l*, *B*, and *lm*, with varying values of *k.*

The relationship between electricity cost, the number of PVs, and their interaction with *k, B*, and *lm* is shown in Figure 6, where *l* takes values of 4, 8, and 16 PVs. The graph illustrates how, as the number of PVs increases, the energy cost decreases. For instance, combination 76 (*k=1, B=1000, l=4, lm=200*) achieved a 7.6% reduction, combination 53 (*k=1, B=1000, l=8, lm=200*) achieved a 20.7% reduction, and combination 26 (*k=1, B=1000, l=16, lm=200*) achieved a 39% reduction, which would correspond to payments of $2,821.24, $2,420.85, and $1,862.54, respectively.

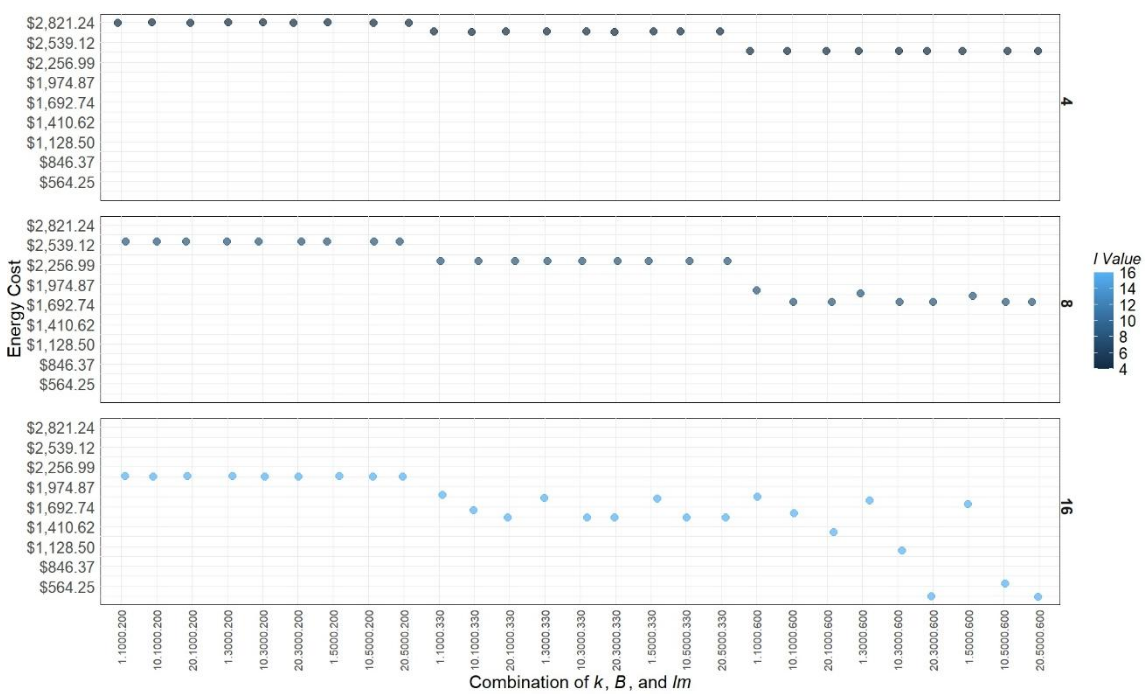


Figure 6. Relationship between energy cost and different combinations of variables *k*, *B*, and *lm*, with varying values of *l.*

Although the number of PVs has an impact, it can also be observed that as the energy production capacity of the PVs (*lm*) increases, better results are obtained in cost reduction, with reductions continuing to decrease as *k* and *B* increase. This assertion is supported by combination 2 (*k=20, B=5000, l=16, lm=600*) and combination 17 (*k=20, B=5000, l=16, lm=200*), where changing the value of *lm* alone resulted in a reduction of 86.3% and 43.5%, respectively, justifying that aside from the number of panels, *lm* plays a crucial role in achieving a significant impact.

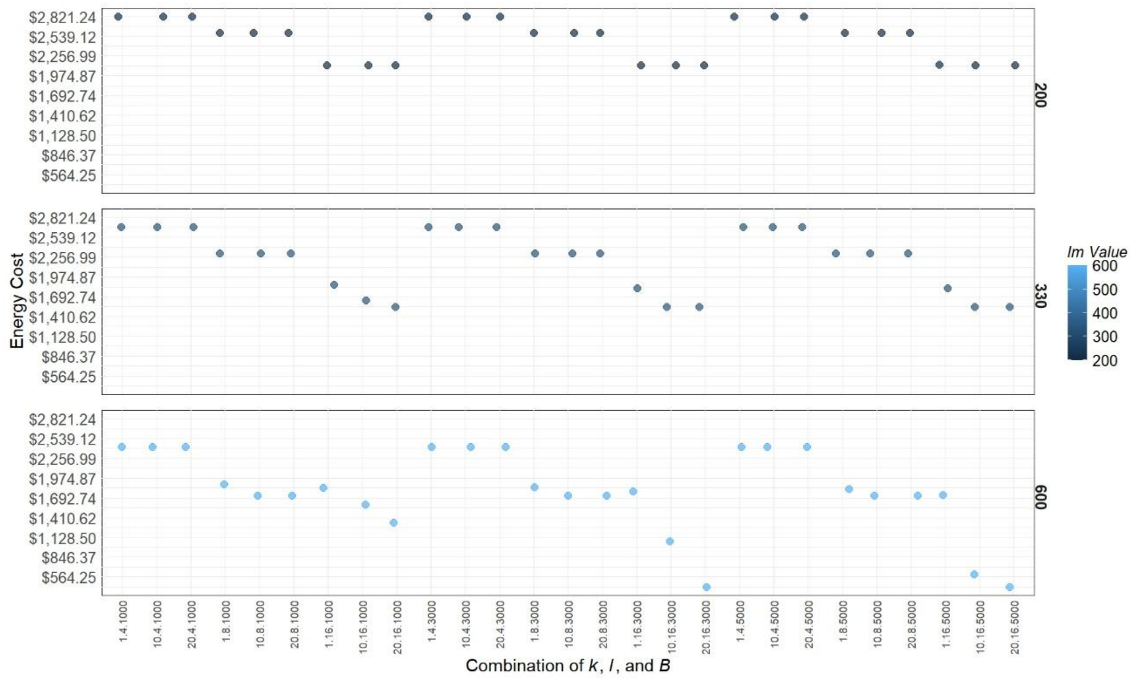


Figure 7. Relationship between energy cost and different combinations of variables *k*, *l*, and *B*, with varying values of *lm.*

Figure 7 illustrates the relationship between energy cost, the energy production capacity of PVs (*lm*), and their interaction with *k, l*, and *B*. When lm is low, the next most impactful factor is *l*, followed by k, and finally *B*. This assertion can be validated with combinations 31, 32, and 33, where *k=20, l=16, and lm=200*, with *B* varying (1000, 3000, and 5000). In all combinations, a 43.5% reduction was achieved, corresponding to a payment of $1,725.45 for the energy service..

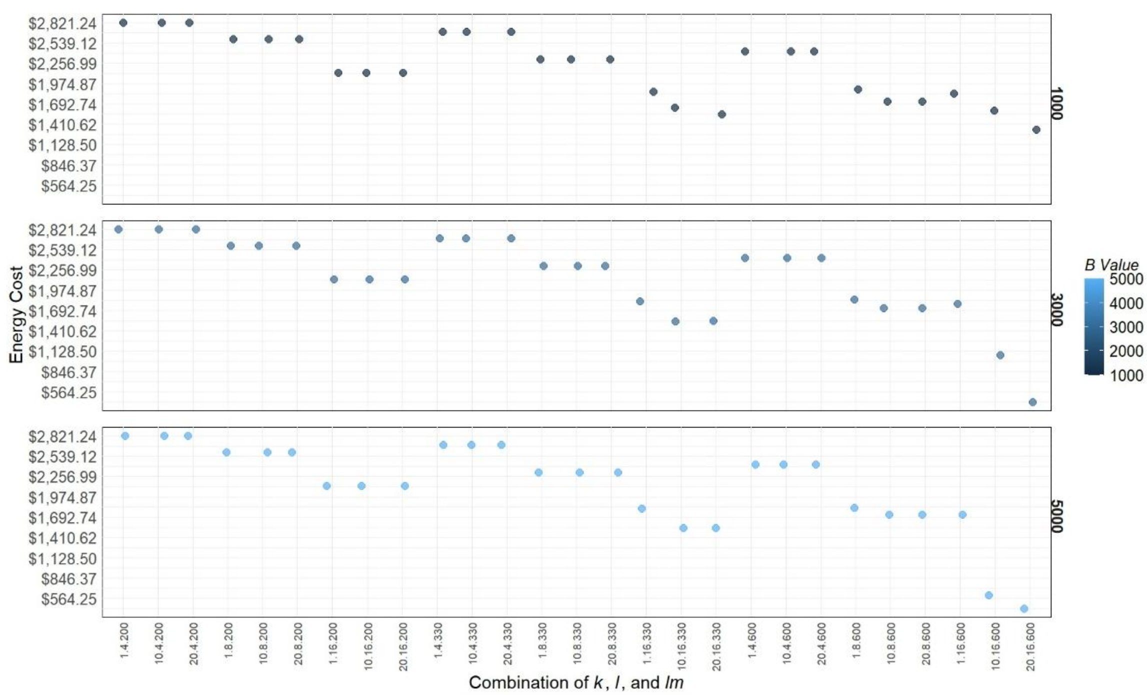


Figure 8. Relationship between energy cost and different combinations of variables *k*, *l*, and *lm*, with varying values of *B.*

When lm is high, and the maximum values of k and lm are maintained, the value of B does not have a significant impact between the medium value of 3000 Ah and the highest value of 5000 Ah, resulting in a reduction of 86.3%. However, when B is at the minimum value of 1000 Ah, the reduction is 56.2%. This leads to the conclusion that the impact on energy cost is primarily dependent on 1) lm, 2) B, and 3) k.

Figure 8 represents the relationship between energy cost, battery capacity (B), and its interaction with k, l, and lm. The best results obtained during the experimentation correspond to cases where 1) lm is high, followed by l, and finally k. This can be verified with combinations 1, 2, and 5, which demonstrate that as the value of B increases, the percentage of cost reduction also increases, whereas when B is lower, the reduction percentage decreases. In the case of combinations 1 and 2, a reduction of 86.3% was achieved, while combination 5 resulted in a reduction of 56.2%. In monetary terms, this corresponds to payments of $419.21 and $1,336.33, respectively.

In the experimentation presented in the article, the application of HOMENERGY-OPT is evaluated under different scenarios, considering each of the constraints to ensure optimal operation. The first constraint ensures that the energy produced, stored, and supplied by CFE is sufficient to meet the demand. Constraints 2 to 5 focus on the energy produced by PV systems, ensuring that the total energy is fully distributed among demand, storage, and surplus (Eq. 7), that h_{lj}^{d} matches the considered value of h_j^d (Eq. 8), that h_j^a corresponds to h_{lj}^{a} (Eq. 9), and that h_j^a corresponds to h'^{a}_{kj}. Constraints 6 to 10 focus on energy storage in k. Equation 11 establishes that a_j^d must be equal to a_{kj}^d, while Equation 12 states that a_{kj}^a must not exceed the capacity of B. Equation 13 ensures that no more energy is extracted than the sum of a_{kj}^a and a_{kj}^d, thereby preserving the integrity of the storage system. Equation 14 guarantees the charge state of each k, considering the energy stored in j and the energy extracted from j to meet demand. Equation 15 considers the initial state of each k, taking into account the known initial charge of each B.
Finally, constraint 11 focuses on the total energy surplus from PV production. It is important to note that, in the conducted experimentation, no surplus value is shown.

The validity of the HOMENERGY-OPT is based on the representativeness and adequacy of the data set used in the experimentation. To evaluate its performance, a planning horizon of 168 hours (one week) was considered, allowing for the capture of variations in residential energy consumption across different periods of the day and week. This interval is widely used in energy management studies as it reflects recurring demand patterns without introducing biases from seasonal factors.

Additionally, the data set includes a representative range of electrical devices commonly found in households, such as refrigerators, televisions, air conditioners, lighting, and daily-use appliances. The combination of these devices allows for modeling different consumption scenarios and assessing the impact of optimization in terms of cost reduction and energy efficiency. Regarding the amount of data used, while it is possible to extend the analysis over a longer period, this study aims to demonstrate the feasibility and effectiveness of the model under controlled and reproducible conditions. Previous studies on energy demand optimization have employed similar-sized data sets to validate efficient management strategies in smart grids (Valencia López, D., (2016), Fernández Carrasco, P. (2023) & Jarrín Vinueza, D. S. (2017)). Furthermore, the experimental design considers different configurations of energy storage and generation, which allows for evaluating the flexibility and scalability of the model.

Finally, it is worth noting that the HOMENERGY-OPT structure allows for its application to larger data sets without loss of accuracy, as its equations and constraints can be adapted to different consumption and energy production scenarios. Therefore, the data set considered in this study is sufficient to demonstrate the model's functionality and benefits, ensuring its applicability in residential environments within smart grids.

The results obtained allow for analyzing the impact of HOMENERGY-OPT on reducing energy costs and decreasing reliance on the external grid. It is observed that the optimal combination of storage and generation significantly contributes to improving system efficiency, achieving a substantial reduction in the cost of consumed energy. In this way, the experimentation validates the applicability of the model in residential scenarios, demonstrating its ability to optimize energy management in smart grids.

8 Conclusions

The development of HOMENERGY-OPT for efficient energy management in smart grids is of great significance, as it has the potential to generate a substantial impact on energy efficiency, sustainability, and the profitability of these systems. Some key benefits include:

- **Reduction in system operating costs**, improving the economic feasibility of SGs and increasing accessibility for a larger number of users.
- **Decreased dependence on the external power grid** and more efficient utilization of energy generated by solar panels and storage systems, ensuring a lower carbon footprint for the system.
- **Balanced and efficient system operation** through optimization of the equilibrium between generated, stored, and consumed energy, maximizing the utilization of available resources.
- **Minimization of excess energy**, which enhances the economic value of the generated power and creates opportunities for additional revenue through the sale of surplus energy.

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