Power System Technology
ISSN:1000-3673

Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

Demand Response to Price Signals in Microgrids: Insights and Future Directions from a Systematic Literature Review

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Abstract:- Microgrids have emerged in the context of promoting greater sustainability and the need for an efficient energy transition to low-carbon sources. The relevance of these networks stems from their ability to offer greater energy efficiency, adjust the internal consumption of their users, reduce costs, and provide energy generation that is less harmful to the environment. This study aims to analyze the factors that influence these responses to fluctuations in energy prices, seeking to offer insights to improve management and promote an efficient and sustainable energy transition. A systematic literature review investigated variations in price signals in microgrids and their impact on users' behavioral patterns. The results highlight that users' acceptance of and reaction to price signals are influenced by various factors, such as their understanding of the economic and environmental benefits, their trust in the technology, and the usability of microgrid systems. In addition, the literature emphasizes the importance of public policies and financial incentives to encourage the adoption of microgrids. Integrating distributed generation and energy storage technologies, combined with dynamic pricing strategies, has proven effective in optimizing energy consumption and reducing operating costs. However, significant challenges remain, including greater consumer awareness and education and developing robust and secure infrastructures.

Keywords: *Systematic Literature Review; Microgrids; Consumer; Price Signals; Demand Response.*

1. Introduction

Microgrids emerged in the context of promoting greater sustainability and the need for an efficient energy transition to low-carbon sources. These consist of energy generation and distribution systems that can operate in isolation or connected to the utility grid [1], establishing an internal energy trading market based on tariffs from Demand Response Programs (DRP)

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ISSN:1000-3673
Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

[2]. The relevance of these networks stems from their ability to offer greater energy efficiency, adjust the internal consumption of their users, reduce costs, and provide energy generation that is less harmful to the environment [3].

Thus, microgrids are considered effective alternatives for a clean and safe energy transition, mainly using renewable sources and promoting sustainable energy development [4–6]. Furthermore, they are defined as clusters of loads, which may or may not be transferable, combined with distributed generation units and energy storage systems to provide energy more efficiently and reliably [7].

The DRP concept was implemented to optimize the operation of these networks. The optimization process is characterized by the ability of industrial, residential, and commercial customers to adjust their consumption patterns in response to price variations defined by the microgrid's internal market [8]. Veloso et al. [9] point out that this model aims to optimize energy consumption based on local patterns, times of use, and generation and distribution parameters, minimizing the operating costs of microgrids.

The effectiveness of DRP depends on the active participation of users in load scheduling, guided by the microgrid controller. Qu et al. [10] identify prices and incentives as variables that highly impact customer participation in DRP based on load adjustment. DRP can be classified into incentive-based or price-based DRP, depending on temporal factors of energy use, and can include Real-Time Pricing (RTP), Critical Peak Pricing (CPP) and Time-of-Use (TOU) [11].

Studies related to microgrid management have been found in the literature. Elazab et al. [12] developed a comprehensive review of these systems, proposing a detailed economic load model for DRP based on price elasticity coefficients. Huang et al. [13] reviewed the fundamental theory of DRP and the Demand Response (DR) potential estimation, seeking to optimize the integrated service strategy used. Karthik & Anand [14] explored energy trading in microgrids in the Peer-to-Peer (P2P) model, proposing using blockchain technology to create smart trading contracts, minimizing problems associated with energy trading. Mishra et al. [15] analyzed protection and grounding methods for microgrids operating on direct current, offering suggestions for these schemes. Schwidtal et al. [16] carried out a Systematic Literature Review (SLR) to examine trading models for agents operating in local energy markets, describe the difference in business models for this type of market and indicate the character of the interactions between participants in this context. In the research by Gržanić et al. [17], variables that encourage flexible prosumer behavior were reviewed, exploring negotiation potentials and decentralization models to foster internal energy transactions. Lu et al. [18] addressed load scheduling models and methods, considering generation and demand sources, focusing on load

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ISSN:1000-3673

Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

scheduling in incentive- and price-based DR environments, and summarized mathematical, heuristic, and data-driven tools for optimizing energy consumption.

This research aimed to fill gaps in understanding consumer response to price signals and their behavior in microgrids. The study aims to analyze the factors that influence these responses to fluctuations in energy prices, seeking to provide insights to improve management and promote an efficient and sustainable energy transition. SLR used a literature survey to support its conclusions and investigate variations in price signals in microgrids and their impacts on users' behavioral patterns. The results addressed the proposed research questions, identified trends and key concepts in the publications analyzed, and highlighted the leading countries of study on the topic. The main contributions of this work are presented below:

- Presenting a comprehensive SLR on the variation of microgrid price signals and users' responses to these variations. Identifying patterns of behavior that are relevant to efficient energy management in microgrids, filling a significant gap in the existing literature;
- Providing a solid conceptual basis and clearly defining the essential terms and concepts related to microgrids and DRP, this approach provides a basis for future research and facilitates understanding of the topics covered;
- Mapping trends in publications on the topic, highlighting key concepts, and identifying the countries where the topic is most studied. Thus, helping to guide future research and policies related to energy management in microgrids;
- Analyze how consumers respond to price signals in microgrids, offering insights into user behavior. This understanding is important for developing management strategies that promote energy efficiency and reduce costs.

The article is organized into 5 different sections. Section 2 contextualizes the energy market in terms of demand and price. Section 3 details the review methodology adopted. Section 4 presents the results of the quantitative analysis and answers the research questions about microgrid consumers' responses to price signals. Section 5 presents the conclusions of the work.

2. Energy market contextualization in terms of demand and price

The energy market is the system that guarantees the continuous supply of electricity to meet demand while maintaining stability and universality in trading prices. According to Ölmez et al. [19], this process covers several stages, from generation to energy retail. Generation can be from renewable sources or fossil fuels, followed by high-voltage transmission to distribution centers. In the distribution stage, electricity is reduced in voltage and supplied to end users through the utilities or new participants, such as aggregators, which make up energy retail [20].

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ISSN:1000-3673

Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

The evolution of distributed energy resources and renewable sources has led to the free energy market, where consumers who generate excess energy can trade it within their networks, known as prosumers [19]. This concept has promoted the decentralization of energy production services, which were previously vertically integrated. In the free market, price regulation is competitive, based on marginal production and distribution costs and the interaction between supply and demand, with the participation of demand aggregators. According to Burger et al. [21], these aggregators are intermediaries that manage flexibilities within the network, grouping consumers and prosumers to optimize energy supply and distribution. They use DR strategies based on historical consumption patterns and locational characteristics [20]. Huynh et al. [22] note that these intermediaries create market contracts and secure the supply and financial settlement.

The introduction of the free energy market has enabled the development of microgrids, which are groups of energy sources, batteries, and electrical loads whose conditions are determined by the network participants [23,24,25]. Thisconcept, derived from the free market, allows microgrids to be managed by aggregators who adjust price signals according to the specific needs of consumers and local infrastructure [26,27].

Based on the concepts presented in references [23,24], a summary was compiled containing relevant information about the characteristics of the energy market discussed, as illustrated in Figure 1.

Figure 1 - Representation of concepts related to energy market types.

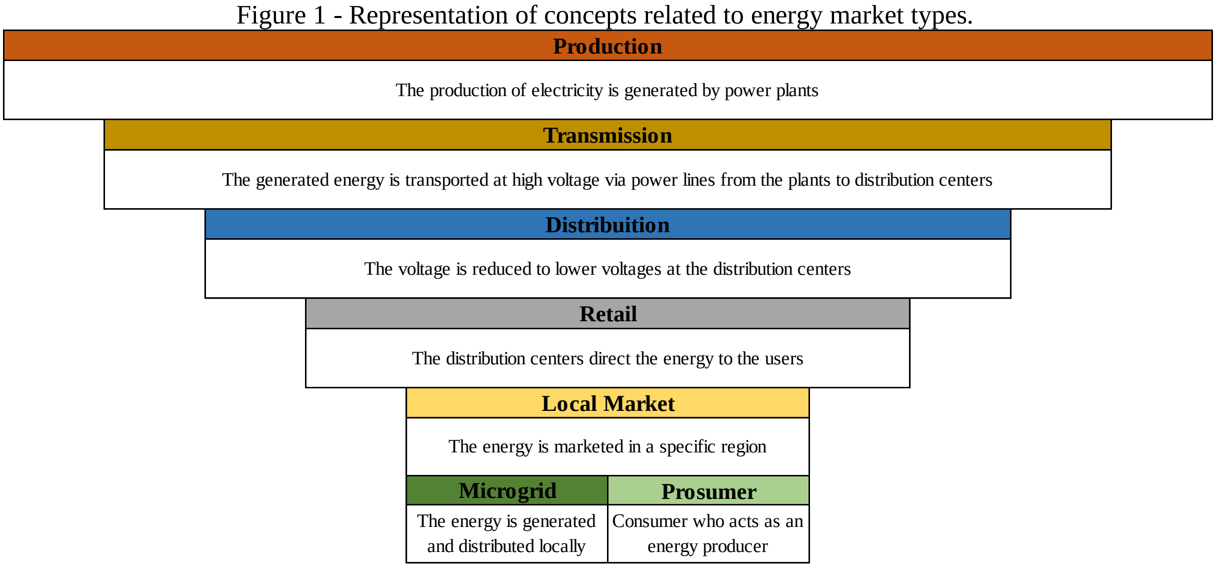

Figure 1 shows a flowchart detailing how the energy market can be divided. Electricity begins its journey in production, where it is generated by power plants. It then enters the transmission phase, being transported at high voltage through transmission lines to distribution centers. At

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ISSN:1000-3673
Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

the distribution stage, the electrical voltage is reduced to lower levels, suitable for residential and commercial use, at the distributors. The energy then passes on to the retail market, where distributors deliver the electricity to end users. On the local market, energy is traded within a specific region, ensuring that supply meets local demand. Finally, in the microgrid/prosumer phase, energy is generated and distributed locally, with consumers also acting as energy producers, contributing to a more resilient and sustainable electricity grid. And it is this latter market that this work focuses on.

With these concepts in mind, this research moved on to the methodological stage, developing a process to identify studies related to microgrids and consumer behavior in response to price signals. This selection process, based on filters established by the authors, will be detailed in Section 3.

3. Methodology

The methodology adopted in this article was based on an SLR. The first step to ensure the feasibility of the study was to define relevant keywords, including: ‘consumer*,’ ‘residential*,’ ‘household*,’ ‘domestic*,’ ‘price*,’ ‘price signal*,’ ‘price fluctuations*,’ ‘demand*,’ ‘elasticity*,’ and ‘microgrid*.’ These keywords were carefully selected to align with the research question presented below:

> Q1. How do consumers respond to price signals in microgrids?
>
> Q2. What is the impact of price signals on demand, considering consumer behavior in microgrids?

These keywords were chosen to understand consumer behavior in response to price changes within an energy microgrid.

With the previous stage defined, two databases were accessed: Scopus and Web of Science. The investigation process on these platforms involved an advanced document search covering the period from all years up to March 25, 2024 (the date the search was conducted). The types of documents were also filtered: articles, conference papers, proceedings, and review articles. The search was further limited to obtaining only documents in English. Table 1 establishes the relationship between the previously described information.

Table 1 - Research investigation process.

Investigation process		
Database	Scopus	Web of Science
Type of survey	Advanced Search	Advanced Search
Search fields	TITLE-ABS-KEY (title, abstract, and keywords)	ALL

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ISSN:1000-3673
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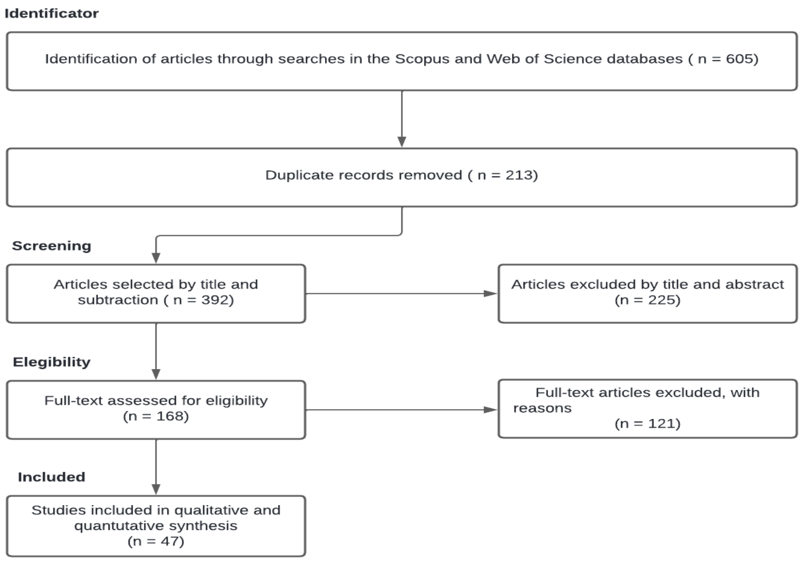
Search string	(((("consumer*" OR "residencial*" OR "household*" OR "domestic*") AND ("price*" OR "price signal*" OR “price fluctuations*”) AND ("demand*" OR “elasticity*”) AND ("microgrid*"))))	(((“consumer*” OR “residencial*” OR “household*” OR “domestic*”) AND (“price*” OR “price signal*” OR “price fluctuations*”) AND ("demand*" OR “elasticity*”) AND (“microgrid*”)))
Search period	Every year until 2024	Every year until 2024
Type of document	Article, Conference Paper, and Review Article	Article, Proceeding Paper, and Review Article

To answer the established research question and characterize the SLR, the research methodology followed the criteria of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), a tool that guaranteed the reliability, organization, and practicality of the information obtained from the analysis of the literature found [28]. With PRISMA it was possible to visualize the steps and processes performed regarding the research phase. Figure 1 illustrates the PRISMA protocol used in this review.

Figure 2 - Prisma protocol used in this research.



In the identification phase, in Figure 1, 605 documents were initially collected through advanced search modes on two platforms: Scopus, which yielded approximately 291 papers, and Web of Science, which produced 314 results. These results were then aggregated and processed using the open-source software R. This software facilitated the removal of duplicate documents, excluding 213 duplicates from the analysis and resulting in a final set of 392 papers for further consideration.

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ISSN:1000-3673
Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

During the screening phase, the first research filter was applied to select articles closely aligned with the proposed research questions. This filter used criteria based on titles and abstracts, leading to the exclusion of 225 publications. In the eligibility phase, 168 publications were deemed relevant to the proposed topic based on the initial screening. Of these, 47 documents were selected for inclusion in the study and used as references to address the research questions. The remaining 121 publications were excluded due to their limited relevance as assessed by the author.

4. Results and discussion

The results of this research were divided into three stages. The first stage refers to the descriptive analysis of the data, the second addresses the research questions, and finally, the insights and future directions are presented. Each of these stages will be evaluated and described below.

4.1 Descriptive data analysis

The study analyzed the evolution of scientific production and found that scientific publications have been produced and published in alignment with society's advancements and adaptations regarding the use of individual and collective renewable energy sources. This evolution subsequently led to the concept and approach of microgrids. Graph 1 illustrates the progression of the relevant scientific production.

Graph 1 - Number of publications versus year of publication of related documents.

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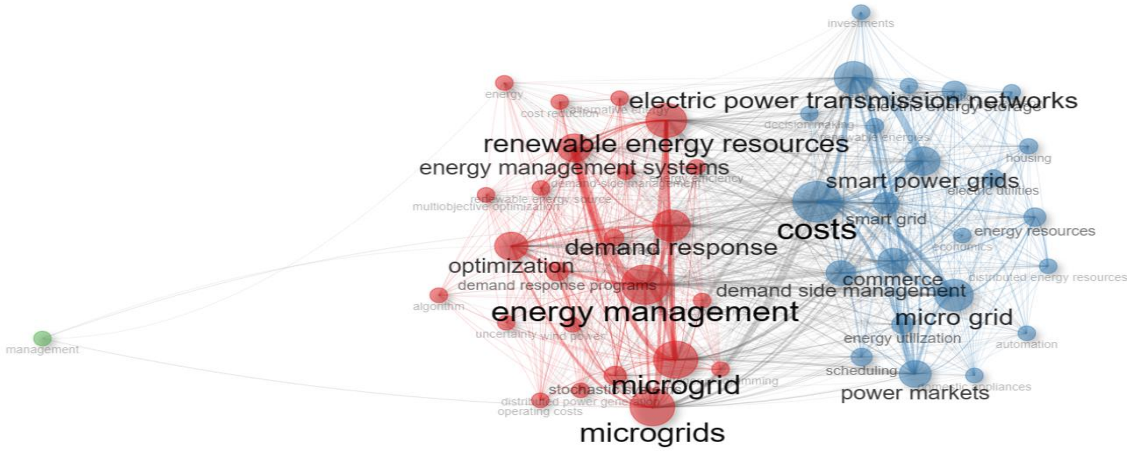
ISSN:1000-3673
Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

Graph 1 shows the evolution of scientific production related to the study topic over time. Based on the works of Zhang et al. [29] and Ziaul Haque Munim, Mariia Dushenko, and Imset [30], a subdivision by 5-year periods was created. During the initial phase of publications (2007-2012), the average was 2.2 publications per year. In the development stage (2013-2018), this average increased to 23.2 publications annually. In the subsequent period (2019-2023), the average rose to 54.6 publications per year, indicating a growing trend in research production in this field. A significant increase in the publication rate has also been observed since 2016, which can be attributed to the intensifying global debate on inequalities in the distribution of costs and benefits of energy transitions and their consequences for countries [31].

Fernández López et al. [32] utilize a keyword co-occurrence network to understand better an SLR, which can help interpret results by indicating the degree of connection between various topics. Figure 3 identifies three groups of topics, showing that two of them have keywords that are well-connected. The dominant group, represented by blue, is related to microgrids, operational maintenance costs, energy trading, and smart grids, among other topics. The second most relevant group, represented in red, is linked to energy management and using renewable sources in microgrid environments, indicating a strong connection between its topics. Additionally, a group represented by green is more related to management in a general context.

Figure 3 - Co-occurrence network of keywords.



Analyzing the data obtained allowed us to verify the number of scientific productions and the number of citations of documents published by country. Graph 2 illustrates the relationship between the number of scientific productions and the total number of citations for the 10 most-cited countries in the published studies. The left vertical axis represents each country's total number of citations, while the right vertical axis shows the total number of scientific publications by country.

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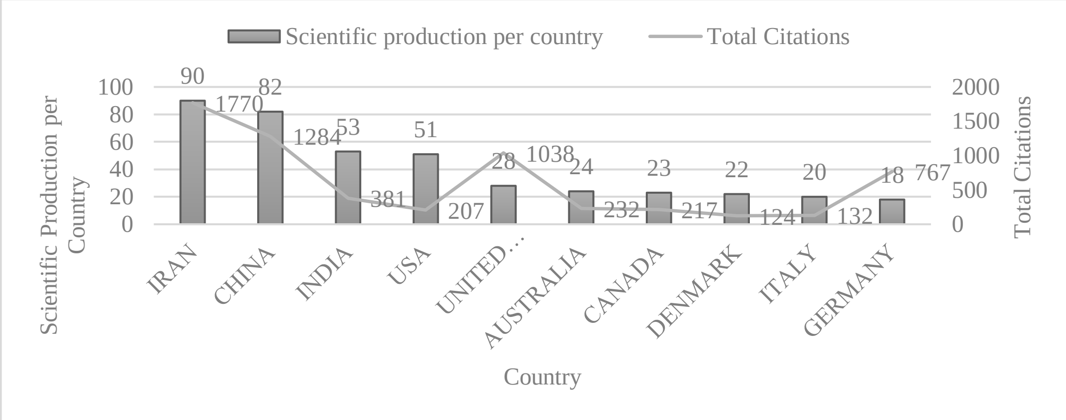
Graph 2 - Scientific production versus total citations of the 10 countries most cited in the documents.



According to Graph 2, China and Iran have the highest number of citations and scientific production, indicating an emerging demand for using models such as microgrids in these regions. A considerable number of citations from the United Kingdom is also observed, which can be explained by its open market in energy trading [33]. This suggests that microgrids could be a competitive alternative to this market model.

Next, the responses to the research questions addressed in the methodology are discussed and presented.

4.2 Research Questions

The research questions evaluating consumer behavior in response to price signals in the context of energy microgrids are presented below as Q1 and Q2. These questions were analyzed based on the 47 documents from the inclusion stage.

Q1. How do consumers respond to price signals in microgrids?

In the study by Seshu Kumar et al. [34], a Mixed Integer Linear Programming (MILP) optimization method is applied to the context of grid-connected microgrids, along with the use of CPP tariffs. The authors observe that user responses to price signals vary. When subjected to incentive based DRP, in most cases, there is no energy export to the utility grid. However, price-based DRPs mean more significant energy exports to the grid. Additionally, the authors report that during peak demand hours, energy import occurs.

Based on the Stackelberg game as an optimization method, Seshu Kumar et al. [34], Genis Mendoza, Konstantopoulos and Bauso [35], and Zareein et al. [36] proposed a microgrid model considering both the connected and disconnected modes of operation. This model includes electric generators as the system's power source for Genis Mendoza et al. [35] and photovoltaic (PV) energy aggregated with wind power in the works by Seshu Kumar et al. [34] and Zareein

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ISSN:1000-3673
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et al. [36]. They proposed real-time pricing in the studies by Genis Mendoza et al. [35] and Zareein et al. [36], and TOU in the context of flexible loads for all three papers. The authors found that there is a change in the incentive characteristics for each situation in which energy generators change their sales values, which results in an adaptation in the amount of load demanded by the consumer according to the intensity of the incentive proposed by the generator. In other words, the consumer's response to price signals is as follows: if an incentive increases, the sales price also increases, causing the consumer to reduce their consumption. In addition, importing more energy from the primary grid directly affects the increase in the sale price, contributing to the consequence previously mentioned. Zareein et al. [36] also noted an increase in the profit of the prosumer agent of the network when this method is used. Kotsis et al. [26] used the same generation type, aggregating flexible and inflexible loads, applied to an optimization technique from a demand aggregator. They identified that an incentive changes peak hours, triggering lower consumption on the part of the consumer. In addition, they observed that applying incentives at alternate times leads to very different load profiles, which makes it challenging to define flexibility standards.

It is also important to mention that different pricing modes affect consumer response. This was demonstrated by Sarker et al. [37]. In their work, a MILP-based optimization model was employed for the demand management of residential flexible loads, studying consumer behavior under two pricing schemes: TOU and RTP, overlaid with PV and wind sources in an off-grid environment. The results show that, in the case of RTP pricing, the peak consumption period occurred between the 15th and 21st hours. In contrast, under TOU pricing, the peak period occurred between the 7th and 23rd hours, indicating a significant difference in the approaches of the two methods. Alilou et al. [38] report a reduction of about 30 percentage points in peak load value when a demand response program based solely on RTP prices is used. This analysis, which considers flexible/inflexible loads with PV generation subjected to an algorithm that tracks competitive market prices, reduced the electricity bills of the involved consumers.

For Yang et al. [39] and Hassan et al. [40], on-grid microgrids were studied using diesel generators, fuel cells, wind turbines, and PV cells with TOU and RTP tariffs in the first study, and only wind and PV production subjected to dynamic pricing in the second. While the first approach uses bi-level stochastic programming for its optimization problem, the second generates results from a Particle Swarm Optimization Technique (P-PSO). The authors report that consumer load demand varies according to the type of pricing adopted. In [39], the authors found that TOU tariffs reduce operational costs, whereas the application of RTP results in more excellent utility for consumers, consequently increasing social welfare. In the case of (36), it was found that user-generated load demand is related to their Comfort Index (CI); for example,

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ISSN:1000-3673

Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

as energy usage increases, users with inflexible loads tend to have a higher profit ratio than consumers with flexible loads in their demand system.

In the context of managing price signals in microgrids, smart tools are increasingly adopted for monitoring and controlling energy consumption. These tools aim to optimize load scheduling, as demonstrated in the studies conducted by Khan et al. [41], Aslam et al. [42], Alhasnawi et al. [43], Adika and Wang [44], and Malik et al. [45].

These studies identified that price signals can be monitored through smart meters for electric energy consumption, which automatically adjusts the load required to operate flexible equipment, increasing or decreasing demand according to the price signals available on the grid. Khan et al. [41] developed a method associated with a dynamic programming model that manages flexible loads in the grid-connected mode. These devices are controlled by a controller that combines demand management actions, resulting in reduced demand in response to high price signals.

Aslam et al. [42] adopt a similar approach, integrating photovoltaic solar panels and wind generators with RTP tariffs, shifting and storing loads during off-peak periods for later sale of the generated electricity during peak times. The decisions to buy and sell are autonomously made by the intelligent system implemented in the studied residences. Alhasnawi et al. [43] explore variables like the abovementioned studies using a two-stage hybrid method for consumption planning, covering TOU, RTP, and CPP tariffs. They achieve significant reductions in peak demand due to implementing consumption control through smart devices.

Adika and Wang [44] present an energy management model combined with demand control in a grid-connected microgrid featuring PV generation. They consider flexible and inflexible loads, with either Dynamic Pricing (DP) or fixed tariff. The results indicate that, although there is a reduction in peak demand, the lack of optimal load scheduling results in suboptimal utilization of the produced PV energy, highlighting the need for efficient energy storage systems. Malik et al. [45] employed the P-PSO method to measure real-time prices, demonstrating that the introduction of intelligent load control systems enhances user comfort. They observed that flexible loads are activated as needed by the proposed algorithm, emphasizing the importance of the Internet of Things (IoT) in microgrid environments.

In the search conducted by Bokkisam et al. [46], price signals are managed through a double auction market, in which the operator sets the price and quantity of energy to compensate the network participants. The method used is PDAM (Periodic Double Auction Mechanism), which defines the dynamics of prices and amounts according to the established schedule for a microgrid market with characteristics such as those described in the previous study [45]. The implementation of this program resulted in consumer responses, who offer their responses based on the situation; in case of choice restriction, self-consumption is prioritized, followed

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ISSN:1000-3673
Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

by energy storage and, as a third option, trading in the market with the distribution network. This work contributed to reducing grid dependence and increasing system autonomy.

Ali et al. [47] developed a simple algorithm for scheduling flexible loads based on TOU pricing, demonstrating that managing price signals can be effective using this type of pricing. In this method, user consumption is monitored. If it exceeds maximum demand limits, a penalty is applied to the tariff, encouraging demand shifting to periods of lower requirement. In the study by Tahersima et al. [48], the management of price signals in a grid-connected microgrid environment, with PV energy generation and using intelligent building controls, is achieved through the balance of supply and demand established at convenient times each day. This method sets a 24-hour price forecast horizon before billing, promoting consumer-side planning and encouraging local energy production for surplus trading by local producers.

Balavignesh et al. [49] propose a MILP method using optimization heuristics, such as genetic algorithms, PSO, and BPSO. This method is applied in an on-grid microgrid with wind and PV generation, analyzing shiftable and non-shiftable loads under two pricing structures: RTP and CPP. The results indicate that, with RTP pricing, prices vary over time, while CPP depends on the duration and peak cost periods, resulting in changes in users' consumption profiles. Liu et al. [50], a k-means-based method is used to cluster similar consumer profiles in an on-grid microgrid. This technique groups consumers based on similarities in their load patterns and flexible load usage times, allowing for pricing according to the identified clusters. Three distinct clusters were created: cluster 1 characterizes customers with higher consumption around midday and evening; cluster 2 encompasses consumers with usage patterns during business hours; and cluster 3 includes customers with elevated consumption compared to other scenarios. From this context, it was identified that these cases offer a viable alternative for effectively managing price signals in microgrids. Given their high domestic energy consumption in Cluster 1, the clients are more suited for implementing DRP. This high consumption would facilitate load management during peak times if these consumers were prioritized for receiving incentives through DRP. In Cluster 2, it was observed that these consumers have a reduced capacity for load reduction due to the predominantly commercial profile of small and medium-sized enterprises, which complicates the implementation of comprehensive load-shifting programs due to the constant need to operate equipment to maintain their establishments. In Cluster 3, it was found that these consumers have limited load adjustment potential due to their lower consumption compared to the other cases analyzed. Considering different consumption contexts, this study directly demonstrated how price signals can be managed in a microgrid.

Numminen et al. [51] and Muhammad Hammad Saeed et al. [52] employ a method based on the real-time DP structure for off-grid microgrids, utilizing transferable loads in a model that combines electrical feasibility analysis with dynamic price simulations. The objective is to

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ISSN:1000-3673
Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

assess whether price variation response can be a potential parameter to improve system performance. In Numminen et al. [51], it was found that, based on this pricing method, the energy price was low 88% of the time and high only 3% of the time, indicating a conservative stance by consumers regarding the timing of consumption. This result corresponds to Muhammad Hammad Saeed et al. [52] findings, where the same pricing model and types of loads were adopted in a microgrid model connected to the power distributor with PV and wind generation. This resulted in a 69.2% increase in consumer profit and an 18.2% reduction in operational costs, reflecting changes in the behavior of the analyzed users in response to alterations in consumption patterns.

Adika and Wang [53] compared systems utilizing autonomous load scheduling in grid-connected microgrids with PV generation and TOU tariffs. With dynamic pricing, they observed a reduction of approximately 4% in costs, indicating that user response is influenced by the scheduling performed by smart devices programmed to meet individual consumer preferences. This result suggests that consumers may not benefit significantly from RTP compared to situations where they are responsible for scheduling their loads. Tiwari et al. [54] implemented a load monitoring strategy based on an intelligent scheduling system for flexible loads in a DP system within a grid-connected microgrid. The results demonstrated a more efficient load distribution, reducing consumption peaks and allowing consumers to adjust their loads effectively, resulting in lower operational costs for the grid.

Lal Karn & Kakran [11], também é utilizado o método de agendamento inteligente de cargas, porém baseando-se em MILP, em um contexto que inclui cargas não programáveis e tarifas como TOU, CPP e RTP, com geração de energia proveniente de fontes PV, eólica, de biomassa e células de combustível. Como resultado, a maioria dos eletrodomésticos foi programada para operar durante os períodos de tarifa mínima, sem comprometer a funcionalidade ideal desejada pelos usuários, o que contribuiu para a redução dos custos operacionais da rede.

Additionally, it is crucial to consider the impact of using energy distribution and storage systems. Silva et al. [55] discuss how these systems influence consumer response to price signals by utilizing a multi-objective DRP mechanism based on user preferences to optimize load transfer. They implemented an RTP tariff system in a microgrid with PV generation, observing a significant reduction in consumed loads and operational costs of the grid. The authors also emphasize the importance of consumer behavior concerning price signals, addressing issues such as thermal and temporal inconveniences. Thermal inconveniences refer to the additional cost of using appliances under unsuitable weather conditions, according to individual consumer preferences. In contrast, temporal inconveniences occur when the use of appliances does not align with expected consumption patterns.

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Table 2 summarizes the main characteristics of the studies analyzed in Q1. This table presents the mode of operation (On-Grid and Off-Grid), types of loads (flexible and inflexible), type of tariff, forms of energy generation, methods employed, results obtained, and user behavior concerning the response to the first research question.

Table 2 – Summary of the main characteristics of the studies evaluated in Q1.

Ref.	On-Grid	Off-Grid	Flexible loads	Inflexible loads	Type of Tariff	Type of Generation	Method	Results	Q1
[34]	Yes	No	Yes	No	CPP	PV and Wind	MILP	Reduced operating costs	In incentive-based programs there is no export of energy
[35]	Yes	Yes	Yes	No	RTP	Electric generators	Stackelberg game	Load shifting according to incentive	Change in consumption patterns
[36]	No	Yes	Yes	No	TOU and RTP	PV and Wind	Stackelberg game	Increased profit for the user agent	Decrease in peak demand
[26]	No	Yes	Yes	Yes	-	PV and Wind	Optimization technique	Incentive changes peak time	Change in load profile
[37]	No	Yes	Yes	No	TOU and RTP	PV and Wind	MILP	Difference in consumption hours for different types of tariffs	Load transfer
[38]	No	-	Yes	Yes	RTP	PV	Price tracking algorithm	Reduction in electricity bills	Reduction in peak consumption
[39]	Yes	No	No	No	TOU and RTP	Diesel, wind and PV generators	Bi-level stochastic programming	TOU reduces costs and RTP increases user comfort	Shifting demand
[40]	Yes	No	Yes	Yes	DP	PV and Wind	PSO	Increased profit and CI	Load demand varies with the pricing model
[41]	Yes	No	Yes	No	DP	PV and Wind	Dynamic programming model	High prices decrease demand	Decreases demand in response to price signals
[42]	Yes	No	No	No	RTP	PV and Wind	Heuristic algorithms and simulations	Load shifting and energy storage	Autonomous decisions via smart device
[43]	Yes	No	Yes	No	TOU, RTP and CPP	PV and Wind	2-stage hybrid method	Intelligent consumption control	Peak consumption reduction
[44]	Yes	No	Yes	Yes	DP and flat rate	PV	Simulations	Unscheduled loads lower PV usage	Decrease in peak demand
[45]	Yes	No	Yes	Yes	RTP	PV and Wind	P-PSO	Increased CI	Activation of flexible loads
[46]	Yes	No	Yes	Yes	Double auction	PV and Wind	PDAM	Greater grid autonomy	Self-consumption, storage and trading
[47]	Yes	No	Yes	No	TOU	-	Optimization Algorithm	Automatic load scheduling	Demand shifting

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Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

Ref.	On-Grid	Off-Grid	Flexible loads	Inflexible loads	Type of Tariff	Type of Generation	Method	Results	Q1
[48]	Yes	No	Yes	Yes	-	PV	Intelligent controls	Incentives for local energy production	Trading surplus energy
[49]	Yes	No	Yes	Yes	RTP and CPP	PV and Wind	MILP	Different behavior for pricing types	Changing consumption patterns
[50]	Yes	No	Yes	No	Pricing scheme	-	K-means	Obtaining consumption profiles	Adapting customers to DRP programs
[51]	No	Yes	Yes	No	RTP and DP	-	Dynamic pricing simulations	Low DP prices	Conservative behavior in electricity use
[52]	Yes	No	Yes	No	DP	PV and Wind	Simulations	Cost reduction	Changing consumption patterns
[53]	Yes	No	No	No	TOU	PV	Autonomous scheduling system	Reduced sales value	Automatic adjustment of consumption in response to price signals
[54]	Yes	No	Yes	No	DP	-	Load control strategy	Reduction in electricity bills	Reducing peak demand and adjusting loads
[11]	Yes	No	No	Yes	TOU, CPP and RTP	PV, wind and biomass	MILP	Cost reduction	Automated scheduling
[55]	Yes	No	Yes	No	RTP	PV	Multi-objective DR	Cost reduction	Load demand reduction

A review of Table 2 shows that 24 studies addressed Q1. Most of these studies utilize the on-grid operation mode with price-based tariffs (TOU, CPP, and RTP) and incorporate renewable energy sources such as PV and wind. Additionally, the application of DRPs directly impacts user response, reducing peak demand and influencing the scheduling of their energy needs. Integrating smart devices in this process also proves helpful in optimizing energy consumption and providing greater comfort to the user. Aslam et al. [42] and Adika and Wang [53] developed an autonomous residential energy management system aimed at minimizing costs for consumers, especially in scheduling loads from PV sources. In their study, Aslam et al. [42] highlight that the system can enhance profits from energy sales by using smart devices to schedule decisions for buying, selling, or storing electricity based on price signals.

In this regard, it was also found that the studies by Mendoza et al. [35] and Zareein et al. [36] use an energy management strategy based on game theory, employing Stackelberg games for flexible loads subject to RTP tariffs. Genis Mendoza et al. [35] highlight that consumers adjust their consumption profiles in response to specific incentives, influencing the main grid's selling prices. Meanwhile, Kotsis et al. [26] conclude that price variations are directly correlated with the load profile of microgrids, demonstrating that incentives are effective in adapting to new consumption patterns when applying incentives. Hassan et al. [40] emphasize that load demand varies according to the pricing model, with consumers adjusting their consumption to reduce

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costs. They observe that DP balances supply and demand, encouraging energy use during periods of greater availability of renewable sources.

In the context of consumer behavior changes in response to DRPs, Bokkisam et al. [46] explain that, when applied, these mechanisms prioritize self-consumption, energy storage, and the sale of the generated surplus. Zareein et al. [36] highlight the variation of DRPs among different types of consumers: residential consumers with high loads have more significant reduction potential. In contrast, small and medium commercial consumers have less flexibility due to their specific operations. This differentiation helps microgrid managers identify which consumers are most suitable to participate in these programs.

Q2. What is the impact of price signals on demand, considering consumer behavior in microgrids?

When evaluating the impacts of price signals on demand considering consumer behavior, a widely used technique by various authors, including Yang et al. [39], Gitizadeh, Farhadi, and Safarloo [56], Li et al. [57], Yang et al. [58], da Silva et al. [59], Rabiee et al. [60], Wu et al. [1], and Mansouri et al. [61] is DRPs. The objective of this tool is to modify load curves and subsequently shift them to avoid hyperconsumption during peak hours. The results indicate that during peak times, when market prices are higher, the load is reduced and/or shifted to times when prices are lower, directly affecting consumer demand. However, each study employs different tools and strategies to implement DRPs. In the study by Yang et al. [39], the authors developed an on-grid microgrid program with RTP and TOU pricing powered by a diesel generator, fuel cell, wind turbines, and PV cells. The bi-level stochastic programming model showed that demand is shifted using the RTP program. When the TOU pricing system is implemented, there is a tendency to store fuel due to combining an electricity generation unit with thermal resources. Similarly, Gitizadeh, Farhadi, and Safarloo [56] used an on-grid microgrid with PV and wind generation and RTP pricing, applying a multi-objective energy management model. Li et al. [57] employed a P2H (Power to Hydrogen) energy infrastructure, where wind energy is converted into hydrogen during periods of high production, and the reverse occurs during periods of low electricity prices in a CHP (Combined Heat and Power) microgrid. The system was designed to monitor flexible loads priced based on incentives, generating electricity through CHP, boilers, microturbines, and absorption chillers. Yang et al. [58] obtained similar results using the Gray Wolf Optimization Algorithm (GWOA) to control consumption through consumer-tied subsidies, working with connected inflexible loads. Da Silva et al. [59] addresses the scheduling of appliances and storage devices with the Non-dominated Sorting Genetic Algorithm III (NSGA-III) in an on-grid environment, introducing RTP for flexible and inflexible loads. The result was an increase in consumption during periods of low prices, improving the system's energy efficiency.

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Rabiee et al. [60] developed a model of Information Gap Decision Theory (IGDT) to analyze a microgrid in both islanded and grid-connected modes, considering uncertainties in energy generation by PV and wind production agents. One of the scenarios proposed in the study involves a grid-connected microgrid with load scheduling, considering the DRP capacity using the strategy addressed by the IGDT technique. The results indicate that the impacts on price signals reflected in consumer behavior are evident, with a demand peak occurring in mid-morning, followed by a sharp drop in demand. Additionally, energy demand is considerably low between 0:00 a.m. and 6:00 a.m., resulting in lower prices and a load shift to this interval through DRP. It is important to note that the program loads are of constant energy, meaning that these loads cannot be reduced but can be shifted from peak price periods to off-peak price intervals.

Wu et al. [1] propose a pareto optimization method to evaluate consumer satisfaction with electricity prices offered by the supplier through the retailer agent in a microgrid operating in islanded mode, with PV and wind generation. Based on game theory concepts, the method aims to mitigate potential selfishness associated with the solutions found. The results indicated that, from the consumer's perspective, flexible loads are shifted through DRP incentives, resulting in an annual savings of 5.4%. On the other hand, for the retailer, there was a 4.3% increase in profit, as well as a significant reduction in generation costs. Regarding the impact of price signals on consumer demand, it was observed that seasonal electricity prices were reduced by 15%, while load demand decreased by 13.4% during peak periods in the islanded mode of the microgrid. These effects were also identified by Nasir et al. [62], who studied on-grid microgrids with wind and PV generation, and in the latter case, with the inclusion of biomass sources and electric vehicle charging stations. Additionally, they mention that the unavailability of generation sources can increase the operational costs of the system.

Mansouri et al. [61] present a MILP model solved using the CPLEX solver for an on-grid microgrid with thermal units and PV panels in its energy generation. The results indicated that implementing DRPs through innovative tools led to a relative reduction in user comfort. This occurred because some electrical devices were scheduled to remain inactive during peak demand periods, which could compromise the availability of these devices in exceptional situations of need. Ye et al. [63] employed a method such as that of Silva et al. [59], utilizing PV and wind generation and TOU pricing for flexible loads. The results demonstrated that consumers with high price elasticity of demand adjusted their consumption behavior according to the established prices, reducing or shifting loads during high-cost periods. This led to a reduction in load variance and an increase in user comfort across different situations.

Datta and Das [64] also found that consumer response to price signals in microgrids occurs through the reduction and/or shifting of loads in response to the price elasticity defined by the

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grid. In their study, the authors implemented a Hybrid Optimization of Gray Wolves and Whales Algorithm (HGWOA) in an on-grid microgrid with PV and wind production. They observed that pricing based on price elasticity and incentive programs optimized system efficiency. Similar results were found by Mansouri et al. [65], who adopted the Conditional Value at Risk (CVaR) method to manage the risk of uncertainties in energy production from wind turbines and gas in a microgrid disconnected from the conventional distribution system. By applying programmable and non-programmable loads, they observed a modification in consumption patterns, increasing user comfort.

Cui et al. [66] propose a method using a CPLEX solver to optimize the operation of Combined Cooling, Heating, and Power (CCHP) microgrids under TOU pricing, considering flexible heating and cooling loads in different power supply systems (electric and gas boilers, cooling unit, and PV unit) during summer and winter seasons. This approach allowed for observing the impacts of price signals on consumer demand. The authors report that heating, cooling, and electricity loads were shifted from daytime/nighttime periods to early morning hours, increasing by 2.81%, 2.95%, and 11.32% in summer, respectively, and by 0%, 2.18%, and 9.84% in winter, respectively, resulting in reduced operational costs.

In [67–69], the authors address the concepts of self-elasticity and cross-elasticity to define the impacts of price signals on consumer behavior through the RTP pricing system. According to Solanki et al. [67], self-elasticity refers to the consumers' ability to reduce the number of loads consumed. In contrast, cross-elasticity is related to shifting loads from certain times to others without affecting user comfort. Zhang et al. [68] applied the Bounded Linear Programming Problem (BLPP) method to an on-grid microgrid under RTP pricing, with generation from PV and wind sources. The authors report that the load profiles and pricing suggested in their study tend to be higher from 6 a.m. to 8 p.m., and energy prices and consumer load demand tend to decrease according to the self-elasticity parameter. In the research by Herenčić et al. [69], an on-grid system based on a double auction method was used. They found lower demand elasticity resulted in lower purchase volumes and prices, indicating reduced energy sales. In contrast, scenarios with higher elasticity resulted in energy sales by the prosumer. Solanki et al. [67] developed an off-grid microgrid model with flexible loads, RTP, and TOU pricing, using price elasticity matrices to calculate demand response levels for different consumer profiles. It was observed that self-elasticity increases with price signal changes, leading to modifications to the consumer load profile.

In the study conducted by Nosratabadi et al. [70], a stochastic pricing-based planning model is proposed within a multi-microgrid energy system, applying a mixed-integer nonlinear programming model. The study investigated a grid-connected microgrid with energy production from boilers and fuel cell units. The impacts of price signals on consumer demand

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occur when prices reach high levels, resulting in the sale of electricity to the utility's distribution system. Conversely, the microgrid purchases electricity from the system when prices are lower. The study also analyzed the influence of seasonal variations on the impacts of price signals on consumer demand, concluding that electricity purchases during the summer result in higher costs compared to winter due to the increased frequency of energy purchases during periods of moderate or high costs for cooling appliances.

Moradi and Ghazizadeh [71] propose a game-theoretic approach based on linear optimization using a CPLEX solver for a grid-connected microgrid, addressing cooperation among users in supplying excess energy to each other. The impacts on consumer demand showed that, with the cooperation method among the agents operating within the microgrid, there is increased energy availability in the internal network, reducing dependence on the external grid. This results in cost reductions, as the price charged by the prosumer in this environment is lower than that of the external grid operator.

Alfaverh et al. [72] considered the uncertainties in household load demand, using PV generation and the flexibility of Electric Vehicles (EVs) for energy storage. They proposed a P2P pricing model based on the relationship between supply and demand, combined with retail prices linked to the import and/or export of energy. The impact of price signals on consumer behavior was observed in the use of batteries and EVs for energy supply during peak demand periods. During low demand periods, PV generation is utilized to recharge these storage units, with excess energy being traded in the P2P market.

In the study by Wang et al. [73] a two-level game optimization model was developed that integrates the energy utility with a user park, considering the behavior of flexible loads in an environment with generation from PV, wind, gas boiler, and microturbines. A gradual user energy preference parameter was introduced to evaluate the impacts of price signals on consumer behavior, quantifying the influence of these parameters on energy consumption, ranging from 20 to 200. When the energy preference factor is below 40, users exhibit reduced requirements for the energy consumption experience, making them more sensitive to variations in price signals. Conversely, when the preference parameters exceed 40, users' sensitivity to the energy experience decreases, increasing load demand as these preference parameters extend.

Azzam et al. [74] propose a method for creating a bi-level framework using a game theory-based algorithm responsible for managing the interaction between the two levels, addressing both the supply side and the demand side in an isolated microgrid powered by distributed generator systems and PV sources, with billing mode-based tariffs. The results showed a reduction in the operational costs of electricity generation. This can be explained by the fact

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Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

that, in the proposed study, the load demand increased during periods when PV energy generation was available. This demonstrates that consumer behavior can be influenced by this availability.

In the Korepanov Vsevolod & Vaskovskaya Tatiana [75] study, the authors apply the concept of game theory to optimize the overall system of a grid-connected microgrid, establishing prices based on market compensation. They highlight the importance of integrating energy storage systems in these environments. The results indicate that the batteries are charged during periods of low demand and, consequently, lower prices. Conversely, during high-demand periods, the stored energy is reintroduced into the grid, aiming to reduce the demanded load or sell excess energy.

Additionally, it is relevant to comment on consumer behavior related to interference associated with non-compliance with load scheduling rules for appliances with flexible loads. The study by Veloso et al. [9] discusses how consumers interfere by using programmable appliances outside of scheduled times, along with other interferences from the system, such as power outages and situations where energy is not produced when it should be. They proposed a method based on the Edge-Fog-Cloud architecture to manage energy demand in a grid-connected microgrid, using power generated by PV and wind systems. This interference can destabilize the microgrid system in which it is integrated.

Table 3 provides a summary of the characteristics of the research addressed in Q2. This table presents the mode of operation (On-Grid and Off-Grid), types of loads (flexible and non-flexible), type of pricing, form of energy generation, methods employed, results, and user behavior for each study related to the response to the second question.

Table 3 – Summary of the main characteristics of the studies evaluated in Q2.

Ref.	On-Grid	Off-Grid	Flexible loads	Inflexible loads	Type of tariff	Type of generation	Methods	Results	Q2
[56]	Yes	No	No	No	RTP	PV and Wind	Multi-objective management model	At peak times, the load was reduced and distributed to other times.	Decrease in peak demand and load shifting
[57]	No	No	Yes	No	incentives	Boiler and Micro-turbine	P2H energy infrastructure	Cost reduction	Demand shifting
[58]	Yes	No	No	Yes	Incentives	-	GWOA	Reduced operating costs	Decrease in peak demand
[59]	Yes	No	Yes	Yes	RTP	-	NSGA-III	Energy efficiency of the microgrid	Shifting demand and potential interference in scheduling
[60]	Yes	Yes	Yes	No	-	Wind and PV	IGDT	Demand shifting	Change in consumption patterns

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Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

Ref.	On-Grid	Off-Grid	Flexible loads	Inflexible loads	Type of tariff	Type of generation	Methods	Results	Q2
[1]	No	Yes	Yes	No	Seasonal tariff	PV and Wind	Pareto optimal	Flexible loads shifted via price incentives	Change in consumption patterns
[61]	Yes	No	No	No	-	Thermal sources and PV	MILP	Decrease in CI	Change in consumption patterns
[62]	Yes	No	No	No	-	PV, wind and biomass	MILP	Increased cost in case of unavailability of sources	Shift in demand
[63]	No	No	Yes	No	TOU	PV and wind	NSGA-II	Reduction in load variance and guarantee of a high user satisfaction rate	Change in consumption patterns
[64]	Yes	No	No	No	Incentives	PV and wind	HGWOA	Efficiency of system optimization	Decrease in peak demand and change in consumption patterns
[65]	No	Yes	Yes	Yes	-	Wind and gas turbines	CVaR	Increase in CI	Change in consumption patterns
[66]	Yes	No	Yes	No	TOU	Electric/gas boilers and PV	MILP	Reduction in operating costs	Shifting demand
[68]	Yes	No	No	No	RTP	PV and wind	BLPP	Increase in load profiles	Demand reduction
[69]	Yes	No	No	No	Double auction	-	LET	Lower elasticity results in lower energy sales	Sale of energy from scenarios with greater elasticity
[67]	No	Yes	Yes	No	RTP and TOU	-	Price Elasticity Matrices (PEMs)	Self-elasticity increases as the price signal increases.	Change in load profile
[70]	Yes	No	No	No	TOU	Boiler	Stochastic programming	Reduction in supply costs	Sale of electricity in periods of high prices.
[71]	Yes	No	No	No	-	-	MILP	Units that did not cooperate incurred higher costs	Peak demand reduction
[72]	Yes	No	No	No	P2P pricing	PV	Energy trading model P2P	During peak demand hours the storage system is used	Change in consumption patterns
[73]	Yes	No	Yes	No	Distribution/operation	PV, Wind and Boiler	Bi-level optimization model	User sensitivity to certain parameters	Change in consumption patterns
[74]	No	Yes	Yes	Yes	Billing tariff	PV and distributed generators	Game theory	Reduced operating costs	Increased demand load at times when PV energy is available

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Ref.	On-Grid	Off-Grid	Flexible loads	Inflexible loads	Type of tariff	Type of generation	Methods	Results	Q2
[75]	Yes	No	No	No	Market clearing	PV and wind	Game theory	Reduced consumption and increased social welfare	Sale of surplus energy by local producers
[9]	Yes	No	Yes	No	-	PV, wind and conventional	Edge Fog Cloud architecture	Interference with load scheduling	Automated load control

Table 3 presents a comparative analysis of different strategies related to Q2. Among the 23 studies analyzed, most focus on on-grid systems, although some also consider off-grid systems relevant for remote areas or consumers aiming for energy autonomy. Various tariff structures are examined, highlighting the diversity of mechanisms to incentivize demand management. As observed in Q1, many studies utilize PV and wind energy generation, reflecting the growing importance of renewable energy sources. The application of various methods in the studies demonstrates the complexity of the demand management problem and the need for advanced optimization and modeling techniques. Additionally, the studies investigate different user behaviors, such as changes in consumption patterns, load reduction, and demand shifting, emphasizing the importance of user behavior in demand management.

Among the studies that analyzed DRPs, Table 3, Veloso et al. [9] stand out by addressing the simplification of user comfort in load scheduling situations. This research implemented a mechanism for integrating household appliances into the residential energy generation system, where a smart device controls and monitors consumption loads. The authors also considered potential interferences in the process, such as power outages, users turning on appliances at times not recommended by DRP programs, and lack of energy generation when needed. The proposed methodology effectively identified these interferences, contributing to the improvement of the system.

Da Silva et al. [59] also address interferences, focusing on user comfort. They refer to these interferences as "time inconvenience" and "thermal inconvenience." Time inconvenience pertains to the cost associated with electricity consumption when appliances are scheduled at times that are not ideal for the user's consumption profile. Thermal inconvenience relates to the consumption cost when appliances are programmed to operate under thermal conditions unsuitable for user comfort. This study aligns with the findings of Mansouri et al. [61], who indicate that the participation of smart homes in DRPs can reduce user comfort indices (CIs). The reduction occurs because some appliances are unavailable during peak demand times, deviating from the user's optimal scheduling. On the other hand, Mansouri et al. [65] conclude that user comfort levels increase due to modifying the demand curve regulated by the DRP

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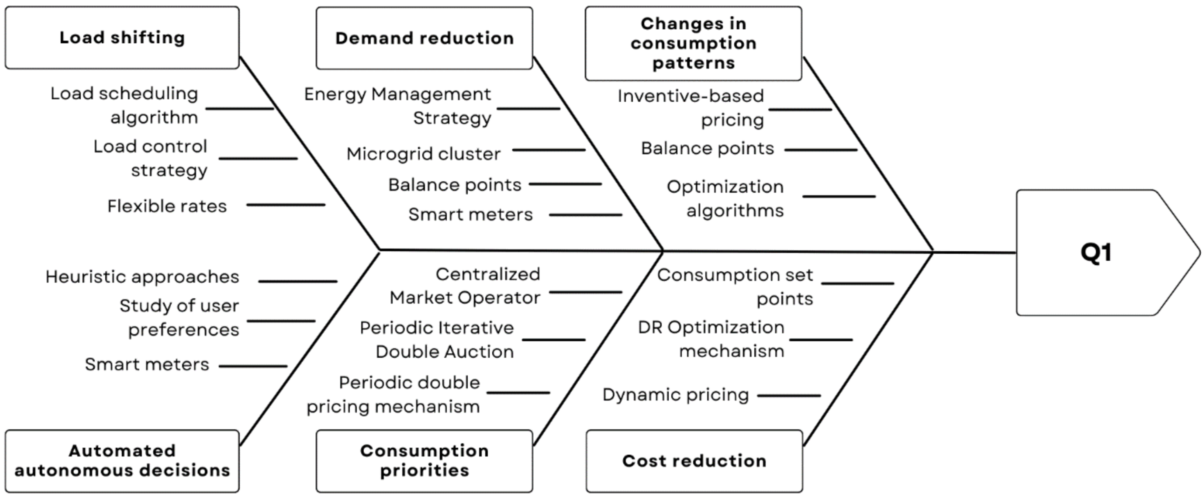
system. With greater available capacity, the microgrid can provide schedules that better meet user preferences established through smart devices.

Solanki et al. [67] and Zhang et al. [68] investigated consumption profiles concerning price-based tariffs, exploring the concepts of self-elasticity and cross-elasticity using different methods. Both studies reached the same conclusion: the ability of consumers to reduce loads (self-elasticity) increases as price signals rise. In contrast, Wang et al. [73] proposed a methodology to analyze consumer sensitivity when exposed to energy preference parameters. They found that when energy parameters are low, users have low consumption requirements and can significantly reduce various loads, showing greater sensitivity to the energy consumption experience. Conversely, when the parameters reach higher levels, user sensitivity to the consumption experience decreases, increasing energy load proportional to the increase in preference parameters.

4.3 Insights and future directions

Exploring the responses and concepts obtained through Q1 and Q2 allowed for filtering and aggregating the contributions of the works found in microgrid management optimization. These contributions were organized and presented to provide insights and directions for future research. The Ishikawa diagram methodology was used to facilitate the interpretation of this information. In this diagram, the strategies applied by the authors studied in this review are considered the leading causes, and specific effects are attributed to each of these causes based on the methods adopted in each study. Figure 4 below illustrates the Ishikawa, or cause-and-effect diagram, related to the central problem identified as Q1.

Figure 4 - Ishikawa diagram for Q1.



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Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

Figure 4 provides a comprehensive and structured view of the leading causes influencing the results of the studies reviewed for Q1, facilitating the identification of areas for future research and improvements in microgrid management. The leading causes identified were classified into six categories: changes in consumption patterns, demand reduction, load shifting, automated autonomous decisions, consumption priorities, and cost reduction.

Changes in consumption patterns were addressed by Genis Mendoza et al. [35] and Balavignesh et al. [49]. The strategies presented by these studies, which influence consumer consumption changes, involve aspects such as incentive-based pricing, characterization of equilibrium points, reference power value, optimization algorithms, dynamic pricing, cost reduction, and the formulation of relationship strategies between consumers and prosumers. Genis Mendoza et al. [35] explain that incentive-based pricing can influence energy consumption in a low-voltage resistive microgrid. Using a Stackelberg game, where the supplier sets a price and consumers adjust their consumption, the study characterizes equilibrium points that ensure system stability. The reference power is dynamically adjusted based on prices, encouraging consumers to reduce consumption during high-demand periods, resulting in cost reductions for both suppliers and consumers. The formulation of relationship strategies between consumers and prosumers is important for optimizing microgrid efficiency and stability, promoting smarter and more sustainable energy use. Balavignesh et al. [49] achieve this result by establishing heuristic optimization approaches for network management. The unique aspect of their work lies in combining generic algorithm methods with PSO and BPSO optimizers, considering that the residential energy management problem studied involved both continuous variables and discrete binary parameters.

Demand reduction was analyzed by Zareein et al. [36], Alilou et al. [38], and Alhasnawi et al. [43]. These studies incorporated concepts based on energy management strategies, microgrid clusters, the utilization of equilibrium points, and the use of smart meters. Zareein et al. [36] achieved demand reduction by defining microgrid clusters using a framework with three agents or layers. The first agent coordinates interactions between the networks, the second manages consumption scheduling, and the third focuses on consumers within this environment. Alilou et al. [38] developed a system that includes both controllable loads (e.g., washing machines, dishwashers, boilers, and vacuum cleaners) and uncontrollable loads (e.g., refrigerators, ovens, TVs, and irons). In this system, the Home Energy Management System (HEMS), aided by smart devices, manages the operational times of appliances considering the constraints imposed by the microgrid conditions. Alhasnawi et al. [43] proposed a two-stage hybrid model that involves household consumption programs with energy generation and storage systems, with the HEMS functioning similarly to that described by Alilou et al. [38]. This model effectively integrates demand response strategies with HEMS capabilities to optimize energy use and reduce operational costs.

Load shifting was addressed in the studies by Sarker et al. [37], Ali et al. ([47], and Tiwari et al. [54], which utilized load scheduling algorithms, load control strategies, and the

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ISSN:1000-3673
Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

establishment of flexible loads. These studies reveal that the application of DRP impacts user behavior by encouraging the shifting of loads from peak hours to periods of lower demand. Sarker et al. [37] argues that, through optimization algorithms like BPSO, consumption loads can be shifted based on the purchase price and consumer preference, keeping the total load demand unchanged. Ali et al. [47] structured their study as a combinatorial optimization problem, scheduling loads over 24 hours. Tiwari et al. [54] propose a load control strategy based on an intelligent scheduling system with dynamic pricing. They simulate a microgrid of four households with different income levels, affecting the quantity and type of appliances present [76].

Aslam et al. [42] and Lal Karn et al. [11] address **autonomous load management decisions** using heuristic methods, user preference studies, and smart devices. Aslam et al.'s [42] research analyzed three scenarios with different combinations of HEMS and microgrids. The analysis revealed that combining an efficient energy management model with microgrids significantly reduces electricity costs. This reduction is possible because autonomous decisions made by smart devices allow for load shifting from peak hours to periods of lower demand, optimizing energy consumption. Thus, integrating HEMS with the microgrid leverages lower-cost periods, enhancing the overall system efficiency. Lal Karn et al. [11] investigated optimal scheduling methodologies for simulated residential, industrial, and commercial load scenarios. The research demonstrated that different DR techniques effectively shift loads among these sectors. It was found that the performance of DR techniques varies according to the specific context and characteristics of the analyzed systems. In other words, the effectiveness of scheduling strategies strongly depends on the conditions of each scenario, highlighting the importance of customizing DR approaches for different environments and energy needs.

The **generation of consumption priority profiles** can be attributed to several factors, including centralized market operators, periodic dual-interaction auctions, and Periodic Dual Pricing Mechanisms (PIDA). Bokkisam et al. [46] explored the establishment of a centralized energy market operator who manages the relationship between the selling price and the quantity of energy offered to the market. This role involves optimizing energy bids and the availability of resources for market participants using PIDA. The centralized market operator performs several vital functions, such as forecasting meteorological data, setting market rules, determining compensation prices based on supply and demand, and maintaining a real-time balance of power distribution within a community microgrid. The operator serves as a supervisory interface for managing interactions among participating agents. Additionally, the study found that the PIDA mechanism decreases reliance on the utility grid and enhances the community's self-consumption and self-sufficiency. These methods are essential for optimizing energy management, ensuring an efficient balance between supply and demand, and improving the stability of the energy distribution system in microgrid-based communities.

Finally, **cost reduction** can be justified using consumption set points, DR optimization mechanisms, and dynamic pricing, as demonstrated by Muhammad Hammad Saeed et al. [52]

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Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

and Silva et al. [55]. Muhammad Hammad Saeed et al. [52] explored the concept of consumption set points, which establish a balance in electricity demand. This approach requires consumers to adjust the set points on their thermostats or allow a broader temperature regulation range, impacting user comfort to some extent. Silva et al. [55] focused on the efficiency of minimizing both the cost related to energy consumption and the inconvenience caused to consumers. They proposed the need for load scheduling, considering user-stipulated preferences. These approaches illustrate how implementing DR strategies and dynamic pricing can optimize energy consumption and reduce costs. At the same time, they aim to balance consumer needs and comfort, highlighting the direct relationship between the cause (cost reduction) and its ramifications (consumption set points, DR optimization mechanisms, and dynamic pricing).

The conclusions from analyzing the causes addressed in the Ishikawa diagram, Figure 4, reveal several valuable insights for microgrid management. Changes in consumption patterns, promoted by strategies such as incentive-based pricing and optimization algorithms, demonstrate that it is possible to balance demand and reduce costs by adjusting consumption in response to dynamic pricing. Demand reduction, achieved through microgrid clusters and smart meters, shows that efficient coordination and managing controllable and uncontrollable loads are crucial for optimizing energy use. Load shifting, facilitated by scheduling and load control algorithms, highlights the importance of moving consumption from peak hours to periods of lower demand, maximizing efficiency, and minimizing operational costs. Autonomous automated decisions, driven by smart devices and heuristic methods, indicate that automation can significantly improve energy management and reduce costs by adapting consumption according to system conditions. Generating consumption priority profiles through centralized market operators and periodic auctions underscores the need to balance supply and demand in real time to maintain microgrid stability and efficiency. Finally, cost reduction, supported by consumption set points and dynamic pricing, emphasizes the importance of adjusting operational parameters to minimize expenses without compromising user comfort. In summary, the various causes addressed reflect the complexity and interdependence of factors that influence the efficiency and sustainability of microgrids, pointing to the need for integrated and customized approaches that consider both technical aspects and consumer preferences to optimize energy management.

Future directions and innovations may include developing more sophisticated dynamic pricing systems and optimization algorithms that consider a more significant number of contextual variables, such as weather conditions and consumer behavior. Integrating emerging technologies like artificial intelligence and machine learning can further enhance autonomous load management and microgrid efficiency. Finally, creating public policies and incentives for adopting these technologies can accelerate the transition to a more sustainable and efficient energy system. Figure 5 presents the Ishikawa diagram related to Q2.

Figure 5 - Ishikawa diagram for Q2.

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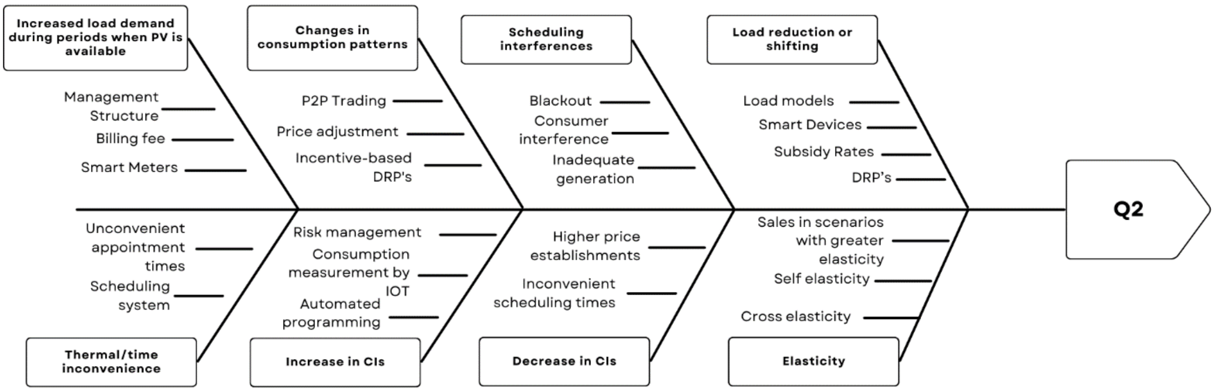
ISSN:1000-3673

Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025



The analysis of Figure 5 allows for the interpretation of the leading causes influencing the results of the studies reviewed for Q2. The most relevant causes in the research context were classified into nine categories: load reduction or shifting, scheduling interferences, changes in consumption patterns, increased load demand during periods when PV is available, thermal/time inconvenience, increase in CIs, decrease in CIs, and elasticity.

Load reduction and shifting are associated with the use of load models, smart devices, subsidy rates, and the implementation of DRPs, as addressed by Gitizadeh et al. [56], Yang et al. [58], Datta et al. [64], and Cui et al. [66]. Gitizadeh et al. [56] combine electricity generation with heat units, creating a DRP-model aimed at modifying load curves. They use time-based tariffs for the analysis, which means electricity rates vary depending on the time of day. This approach encourages consumers to adjust their energy consumption to periods when electricity is cheaper, contributing to more efficient energy demand management. Yang et al. [58] developed a simulation model incorporating subsidy rates applied to consumers, using DR and interruptible load scheduling to create four distinct scenarios for analysis. The model considers the degree of user participation, noting that as participation decreases, the adjustable load also reduces. The study aims to understand the relationship between consumer involvement in demand management strategies and the efficiency of tariff policies to optimize energy consumption and achieve the objectives of subsidized rates. Datta et al. [64] obtained similar results through simulations on a five-microgrid test system. Three residential microgrids formed a coalition in this system, while the two industrial microgrids formed another. Energy control was based on price elasticity and incentives offered to consumers. Cui et al. [66] used an optimization model to operate CCHP microgrids efficiently. The authors reduced energy consumption by analyzing different auxiliary heating sources and selecting the most efficient one, applying mathematical modeling in various scenarios in the proposed simulation. These studies demonstrate that DRPs, smart devices, subsidies, and load models can effectively contribute to load reduction and shifting. Considering the specific variables of each scenario, implementing these strategies is crucial for optimizing energy management in microgrids, promoting energy efficiency, and reducing operational costs.

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Veloso et al. [9] addressed the issue of **load scheduling interferences**, arguing that such interferences can occur due to power outages, inadequate generation, or actions by the users themselves. To tackle this problem, the authors developed an IoT framework capable of recognizing potential interferences caused by consumers in scheduling their loads, verifying whether the programmed consumption times are being adhered to. This approach allows for precise monitoring and efficient management of energy consumption, contributing to the stability and reliability of the electrical system.

Alfaverh et al. [72] observed **changes in energy consumption patterns**, identifying their causes in P2P trading, price adjustments, and incentive based DRPs. The P2P energy trading model proposed in the study considers the negotiation of surplus PV generation and the energy stored in electric vehicle batteries during their charge and discharge cycles. This model is designed based on the relationship between energy demand and supply and the relationship between RTP and feed-in tariffs. The goal is to ensure equity in market participants' actions, guaranteeing that all have fair opportunities to negotiate and adjust their energy consumption and offerings. This system promotes balance in the energy market, encouraging active consumer participation and contributing to the efficiency and sustainability of the electrical system.

Energy demand during periods when PV energy is available was presented by Azzam et al. [74]. They relate this trend to the energy management framework and the use of smart meters. The study considers the variability and discontinuity of PV energy generation, using historical data and weather conditions to predict its availability. The energy management framework described in the work allows for predictive load management, adjusting energy consumption according to the forecasted availability of PV energy. Smart meters facilitate this process by monitoring energy consumption and generation in real-time, enabling dynamic load adjustment to maximize the use of available solar energy. In summary, the approach aims to optimize energy consumption by fully utilizing PV generation, reducing dependence on non-renewable energy sources, and improving the overall efficiency of the electrical system.

Silva et al. [59] identifies **thermal or time-related interferences** related to load scheduling and its impact on consumer satisfaction with the service. The authors explain how interferences arise due to inconvenient load scheduling times and the structure of the scheduling system. Additionally, the proposed simulations allowed for an analysis of how different family compositions and regional contexts affect the effectiveness of load scheduling and consumer satisfaction with the service.

The **increase in CI** was found in the works of Mansouri et al. [65] and Korepanov Vsevolod et al. [75], attributed to using risk management tools, IoT-based consumption measurement, and automated scheduling. Mansouri et al. [65] developed a risk management method associated with uncertainties in energy generation, scheduling loads in different risk tolerance contexts. These contexts were designed to observe how varying risk aversion levels influence

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Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

load scheduling and user comfort. Korepanov Vsevolod et al. [75] achieved similar results using different pricing mechanisms and active energy storage. Additionally, they developed a model to quantify user comfort based on indicators such as energy availability, price stability, and the system's capacity to remain unaffected by supply interruptions. In contrast to previous results, Mansouri et al. [61] reported that the participation of smart homes in DRP could, in some cases, reduce user CI. This reduction in comfort is due to the establishment of higher prices and the scheduling of loads at times that do not align with consumer preferences. The research indicates that this phenomenon can be attributed to the inactivity of certain appliances directly related to CI during peak periods. This inactivity results in deviations from the optimal programs for the user, compromising overall comfort. These studies demonstrate that integrating advanced technologies and risk management strategies can increase user satisfaction and comfort, optimizing energy management and system stability.

Finally, the **elasticity** identified in the studies by Solanki et al. [67] and Nosratabadi et al. [70] is explained by analyzing energy sales in higher user elasticity, self-elasticity, and cross-elasticity scenarios. While Solanki et al. [67] focus on consumer responses to different real-time pricing characteristics, Nosratabadi et al. [70] explore elasticity through a comprehensive model that considers consumer satisfaction and responses to stochastic pricing in a microgrid environment. Both studies aim to understand better how energy price variations affect consumer behavior and demand elasticity.

Analyzing the causes presented in the Ishikawa diagram for Q2 reveals several significant implications for energy management, highlighting the need for adaptive and integrated strategies. The reduction and shifting of load, scheduling interference, and changes in consumption patterns demonstrate that implementing smart devices, time-based tariffs, and demand response programs is crucial for efficient and sustainable energy management. The growing demand for PV energy, combined with thermal/time interference, necessitates a dynamic approach that maximizes the use of renewable sources while minimizing inconvenience to consumers. The impact on comfort levels and demand elasticity underscores the importance of considering the end-user's well-being when developing pricing policies and energy management strategies. The novelty lies in the increasing use of IoT technologies and P2P trading models, which offer greater control and flexibility for providers and consumers. Future directions should focus on optimizing the interaction between intelligent systems and the continuous adaptation to consumer preferences and developing more adaptive solutions to enhance energy efficiency and user satisfaction. The combination of these approaches promises to improve energy management and promote greater sustainability and resilience in electrical systems.

5. Conclusion

The SLR on user responses to price signals in microgrids has revealed relevant insights for effectively developing and implementing these emerging technologies. The results highlight

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Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

that various factor, such as the understanding of economic and environmental benefits, trust in the technology, and the usability of microgrid systems, influence user acceptance and reaction to price signals.

Additionally, the literature emphasizes the importance of public policies and financial incentives to promote the adoption of microgrids. Integrating distributed generation and energy storage technologies, combined with dynamic pricing strategies, has proven effective in optimizing energy consumption and reducing operational costs. However, significant challenges remain, including the need for greater consumer awareness and education and the development of robust and secure infrastructures.

Future research should focus on empirical studies that assess the impact of different pricing models and user engagement strategies in varied contexts. In summary, the adoption of microgrids and the positive user response to price signals have the potential to reshape the energy sector, driving greater sustainability and efficiency. Continued investigation and collaboration among governments, businesses, and consumers will be crucial for the success of this energy transition.

Acknowledgment

The authors would like to express their gratitude to the Programa de Pós-graduação em Engenharia de Produção (PPGEP) at the Universidade Federal de Santa Maria, the Instituto Nacional de Ciência e Tecnologia em Geração Distribuída de Energia Elétrica (INCT-GD), and the Laboratório de Modelagem e Otimização de Sistemas (LaMOS-UFSM). This work was supported by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) - Finance Code 001, and the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq).

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Power System Technology
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Received: 16-01-2025 Revised: 05-02-2025 Accepted: 22-03-2025

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