# Customer Centric Price-Based Energy Flexibility Estimation for Thermostatically-Controlled Loads

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***Abstract*—This paper assesses the potential energy flexibility of thermostatically controlled loads from a customer-centric pricing perspective. The power system's evolving landscape, marked by efforts towards grid decarbonization and the proliferation of grid edge resources for diversified energy sourcing, has introduced significant complexity to grid operations. This complexity is exacerbated by unpredictability and variability in consumer demand due to changes in weather patterns (seasonal and unexpected), economic conditions, and preferences. This challenge highlights the need for more flexibility in the grid to manage the changes in demand and supply. When optimally managed and controlled, thermostatically controlled loads represent flexible loads. They offer significant potential to provide essential grid services (such as peak load management), thus improving the grid's reliability and resilience. This paper estimates the inherent flexibility potential of HVAC systems of individual residential houses from a pricing standpoint, evaluating their suitability for demand response initiatives. Using data from Phoenix, Arizona, three tariff models from SRP Electric Utility are tested for energy and cost savings. The flexible estimation is formulated as a linear optimization with customer bill minimization. The results emphasize the importance of grid edge resources for enhancing energy flexibility and highlight the need to tailor pricing strategies to different customer segments for optimal results.**

***Keywords*—Thermostatically Controlled Loads, Flexibility, Estimation, Demand Response, Electricity Pricing.**

## I. Introduction

Over the past decade, traditional power distribution infrastructure has swiftly evolved, driven by government policies and initiatives towards grid decarbonization, advancement in smart grid technology, and the increasing drive for renewable energy options like electric vehicles, rooftop photovoltaic systems, and energy storage solutions [1]–[3]. These factors have informed the change from traditional distribution systems to active distribution grids that can accommodate bi-directional power flow and support a decentralized energy generation structure [4]. Furthermore, the rise in adverse weather events and the escalating impact of climate change, characterized by global temperature increases and abrupt weather fluctuations, pose significant challenges to operating, monitoring, and controlling distribution systems. Consequently, the electrical network is compelled to adapt to unforeseen scenarios, placing increased strain on grid infrastructure [5], [6]. In response to these changing dynamics, there is a pressing need for greater flexibility within the distribution grid. This flexibility is crucial to enhance adaptability, maintain grid functionality, and ensure system reliability in the face of evolving challenges and opportunities in the energy landscape [7].

Thermostatically controlled load units, including air conditioning systems, space heaters, refrigerators, and water heaters, play a significant role in building energy consumption, accounting for approximately 35% of total energy use [8]. These loads are flexible as they can be monitored and controlled strategically to shift electricity demand, offering ancillary services during peak events [9], [10]. Therefore, accurately assessing these systems' flexibility is essential for improving grid efficiency and evaluating the effectiveness of energy-saving measures at the building level. Estimating energy flexibility is becoming increasingly important as it enables system operators to utilize flexible loads to meet various grid service requirements, such as avoiding capacity constraints and preventing costly grid outages [11], [12]. Utilities can also reduce operational costs by characterizing and optimizing flexible loads to assist in planning day-ahead generation dispatch and peak load curtailment, obtaining a better balance between demand and supply, and improving overall system efficiency [12], [13].

Several approaches for estimating energy flexibility have been explored in the literature. For instance, setpoint adjustments are utilized in [14] to measure flexibility in commercial and residential loads for demand response purposes. [15], [16] employed data-driven approaches to assess energy flexibility potential in residential load users. [17] quantified flexibility in thermostatically controlled loads using scenario-based approaches derived from power flexibility distribution functions. In [18], a home energy management system with model predictive control is employed to quantify flexibility in residential buildings, formulating flexibility bands and dispatching resources upon request. Also, [19] implemented a distributed controller involving a central load aggregator and building-level controllers to coordinate thermostatically controlled loads. Furthermore, [20] examined the application of adaptive model-free optimal control strategies for thermostatically controlled loads. Despite these advancements, energy stakeholders continue to pursue methods for quantifying demand flexibility, given its growing significance in modern distribution grid operations [21].

This paper assesses the potential energy flexibility of residential grid-interactive cooling systems from a customer-centric pricing perspective to optimize energy consumption and enable effective energy management. It aims to minimize energy costs by considering the household's cooling needs and different pricing strategies. The study explicitly targets a hot climate region in Arizona, utilizing the local utility's pricing structure. The main contributions of this paper are:

- Develop a grid-interactive cooling system model for a residential home to estimate flexibility potentials.
- Test and compare the energy flexibility and cost savings offered by different pricing models from an existing utility.
- Evaluate the significance of grid edge resources, including PV and battery storage, using different scenarios to observe how they enhance the flexibility available.

The rest of the paper is structured as follows: Section II presents background and problem formulation, Section III provides the simulation results and discussion, and finally, Section IV concludes the study.

## II. Background and Problem Formulation

### *A. Cooling Load Energy Flexibility Estimation*

Cooling load flexibility is the amount of variation in energy consumption that a cooling device can accommodate while maintaining customer requirements. Electricity users with grid-interactive cooling devices can shift energy consumption to times when electricity costs are cheaper and can also use less energy when the grid is at peak demand while maintaining preset comfort levels. In this study, the primary goal is to quantify and optimize the potential level of flexibility, specifically in terms of cost and energy savings from the customer's perspective, based on energy pricing structures for every hour of the day. The flexibility available is the savings in energy between a base case consumption $P_{bc}$ and a customer-centric controlled energy consumption $P_{wc}$ as shown in (1) and (2).

$$\Delta P^t = P^t_{\text{bc}} - P^t_{\text{wc}} \quad \forall t \in \{1, 2, \ldots, 24\} \tag{1}$$

$$\text{Flex} = \Delta P = \sum_{t=1}^{24} \Delta P^t \quad \forall t \in \{1, 2, \ldots, 24\} \tag{2}$$

$P_{bc}$, the base case power consumption, represents the typical energy usage during regular operations. This value is derived from historical data through regression or machine learning models trained on predictor variables like outdoor temperature, humidity, cloud cover, and other climate indicators. It serves as the expected energy consumption for an average residential customer at specific time intervals. $P_{wc}$, the power consumption with control, reflects a customer's energy usage when employing a customer-centric control strategy to minimize energy expenses. This controlled consumption considers outdoor weather conditions, room temperature, room setpoint, electricity prices, and cooling system capacity. To maximize flexibility potential at each time step ($\Delta P^t$), we introduce an optimization problem to minimize controlled consumption ($P_{wc}$) while maintaining the desired comfort level. The goal is to minimize $P_{wc}$ and examine the associated costs based on different pricing structures. Therefore, the objective function is defined in (3) as minimizing the cost of energy consumption subject to the desired comfort level and cooling system requirement constraints.

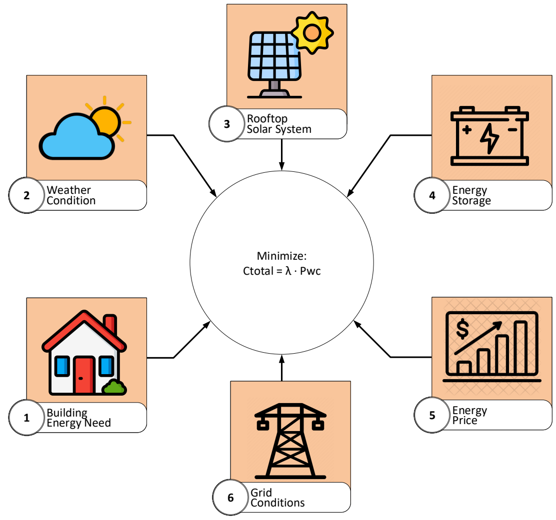



Fig. 1: Grid Interactive Cooling System

$$\text{Minimize:} \quad C_{total} = \boldsymbol{\lambda} \cdot \mathbf{P}_{wc} \tag{3}$$

Where:

$$\boldsymbol{\lambda} = \begin{bmatrix} \lambda^1, & \lambda^2, & \cdots & \lambda^{24} \end{bmatrix}$$
$$\mathbf{P}_{wc} = \begin{bmatrix} P^1_{wc}, & P^2_{wc}, & \cdots & P^{24}_{wc} \end{bmatrix}$$

### *B. Grid Interactive Cooling System Modeling*

*1) Building Occupants Need:* The building occupants' need is modeled as a human comfort constraint in (4), (5). The room temperature must be maintained within a boundary to keep the occupants comfortable and safe as they set their tasks. Therefore, at any time $t$, the room temperature must be within bound $\{T_{\text{min}}, T_{\text{max}}\}$. Also, the change from one hour of the day to the next must not be so drastic that it makes the occupants uncomfortable.

$$T^{\text{min}}_{\text{in}} \leq T^t_{\text{in}} \leq T^{\text{max}}_{\text{in}} \tag{4}$$
$$|T^{t+1}_{\text{in}} - T^t_{\text{in}}| \leq \Delta T^{\text{max}}_{\text{in}} \tag{5}$$

*2) HVAC System Model:* The cooling system constraint is presented in [22]. The indoor temperature at the next time step is a weighted sum of the current indoor temperature and the amount of cooling provided by the HVAC system. The weight is considered as the factor of inertia property of the building, which defines the rate at which indoor temperature is affected by that of the environment.

$$T^{t+1}_{\text{in}} = \varepsilon_{\text{HVAC}} T^t_{\text{in}} + (1 - \varepsilon_{\text{HVAC}}) \left( T^t_{\text{out}} - \eta_{\text{A}} P^t_{wc} \right) \tag{6}$$

$$0 \leq P^t_{wc} \leq P_{\text{max}} \tag{7}$$
$$T^{\text{min}}_{\text{in}} \leq T^t_{\text{in}} \leq T^{\text{max}}_{\text{in}} \tag{8}$$

*3) Weather Condition Model:* The outdoor temperature is considered for July, Arizona's peak summer period, when the cooling demand is at its maximum. The data used for the 24-hour time is obtained from the Phoenix Sky Harbour International Airport Station [23].

*4) PV System Model:* The rooftop solar PV constraint is presented in [22]. The output power of the PV system is obtained from the available solar irradiance $R^t_{\text{pv}}$ as defined by (9). The output power is also a function of the surface area of the PV array $A_{\text{pv}}$ and the transformation efficiency $\eta_{\text{pv}}$.

$$P^t_{\text{pv}} = R^t_{\text{pv}} A_{\text{pv}} \eta_{\text{pv}} \tag{9}$$

*5) Battery Storage System Model:* The battery energy storage system constraint is presented in [22]. The charging and discharging capacity $(P_{\text{BSC}}, P_{\text{BSD}})$ must be greater than or equal to 0 but less than or equal to the capacity of the battery $P_{\text{BSmax}}$ as in (10) and (11). the state of charge of the battery must be within $\{B^{\text{min}}_{SoC}, B^{\text{max}}_{SoC}\}$ as in (12). Also, the battery's charge state follows as defined in (13).

$$0 \leq P^t_{\text{BSC}} \leq P_{\text{BSmax}} \tag{10}$$

$$0 \leq P^t_{\text{BSD}} \leq P_{\text{BSmax}} \tag{11}$$

$$B^{\text{min}}_{SoC} \leq B^t_{SoC} \leq B^{\text{max}}_{SoC} \tag{12}$$

$$B^{t+1}_{SoC} = B^t_{SoC} + \frac{P^t_{\text{BSC}} - P^t_{\text{BSD}}}{P_{\text{BSmax}}} \tag{13}$$

### C. Pricing Structure Implementation

The electricity pricing model is broadly classified into time-of-use and tier-structure pricing. The time-of-use pricing model is such that the electricity price varies depending on the time of the day, thus reflecting the variability of demand and supply on the grid throughout the day. For example, during peak hours, the electricity price may be higher due to high demand, and during off-peak hours, the price is reduced to allow consumers to use the excess capacity. On the other hand, tiered structure pricing sets electricity prices in tiers based on consumption levels. The first tier charges a lower rate for the initial consumption, with subsequent tiers imposing higher rates for additional usage. The pricing models used in this study are cloned from SRP Electric Utility, Phoenix, Arizona [24].

*1) TOU Price Plan:* In the Time of Use (TOU) price plan, the daily peak hours are between 2 pm and 8 pm. As a result, the energy price during those hours is higher than that of the rest. The total energy cost is calculated as follows.

$$C_{total} = \sum_{t=1}^{24} \lambda^t P^t_{wc} \tag{14}$$

where,

$$\lambda^t = \begin{cases} 0.0906, & \text{for } 1 \leq t \leq 14 \\ 0.2585, & \text{for } 15 \leq t \leq 20 \\ 0.0906, & \text{for } 21 \leq t \leq 24 \end{cases} \tag{15}$$

*2) EZ3 Price Plan:* In the EZ3 price plan, the daily peak hours are between 3 pm and 6 pm. As a result, the energy price during those hours is higher than that of the rest. The total energy cost is calculated as follows.

$$C_{total} = \sum_{t=1}^{24} \lambda^t P^t_{wc} \tag{16}$$

where,

$$\lambda^t = \begin{cases} 0.1029, & \text{for } 1 \leq t \leq 15 \\ 0.3620, & \text{for } 16 \leq t \leq 18 \\ 0.1029, & \text{for } 19 \leq t \leq 24 \end{cases} \tag{17}$$

*3) Residential Demand Price Plan:* In the residential demand price plan, the total energy cost comprises the energy charge per kilowatt-hour (kWh), and the demand charge, as a tiered rate charge, is based on the maximum power consumed within a single interval. Customers are encouraged to distribute their electricity usage throughout the day, reducing the energy required at once. The total energy cost is calculated as follows.

$$\begin{aligned} C_{total} =& C_{energy} + C_{demand} \\ =& \sum_{t=1}^{24} \lambda^t P^t_{\text{wc}} + m_a \lambda_a \max(P^t_{\text{wc}}) \\ &+ m_b \Big( \lambda_a P_a + \lambda_b \big( \max(P^t_{\text{wc}}) - P_a \big) \Big) \\ &+ m_c \Big( \lambda_a P_a + \lambda_b (P_b - P_a) + \lambda_c \big( \max(P^t_{\text{wc}}) - P_c \big) \Big) \end{aligned}$$

subject to:

$$m_a + m_b + m_c = 1, \quad m_a, m_b, m_c \in \{0, 1\} \tag{18}$$

where,

$$\lambda^t = \begin{cases} 0.0588, & \text{for } 1 \leq t \leq 14 \\ 0.0798, & \text{for } 15 \leq t \leq 20 \\ 0.0588, & \text{for } 21 \leq t \leq 24 \end{cases} \tag{19}$$

$$m_a = \begin{cases} 1, & \text{if } 0 < \max(P^t_{\text{wc}}) \leq P_a \\ 0, & \text{otherwise} \end{cases} \tag{20}$$

$$m_b = \begin{cases} 1, & \text{if } P_a < \max(P^t_{\text{wc}}) \leq P_b \\ 0, & \text{otherwise} \end{cases} \tag{21}$$

$$m_c = \begin{cases} 1, & \text{if } P_b < \max(P^t_{\text{wc}}) \leq P_c \\ 0, & \text{otherwise} \end{cases} \tag{22}$$

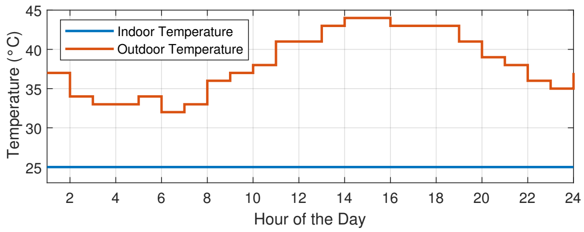
$$P_a = 0.5 P_{\text{max}}, \quad P_b = 0.8 P_{\text{max}}, \quad P_c = P_{\text{max}} \tag{23}$$

$$\lambda_a = 1.886, \quad \lambda_b = 3.502, \quad \lambda_c = 6.718 \tag{24}$$

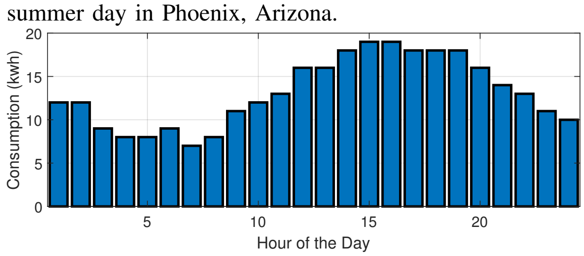
## III. Simulation and Results

### A. Base Case Modeling

This study focuses on the cooling load of residential customers. The baseline energy consumption profile is derived from a business-as-usual scenario. In this scenario, the consumer maintains a fixed indoor temperature of 25°C

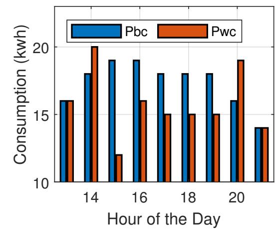



(a) In the base scenario, the target indoor temperature is set at 25°C, and the outdoor temperature corresponds to a hot summer day in Phoenix, Arizona.

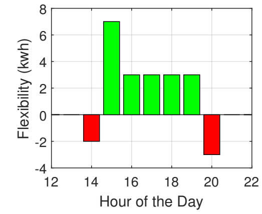



(b) The energy consumption profile for the base case is derived over 24 hours, utilizing a fixed target indoor room temperature set point of 25°C

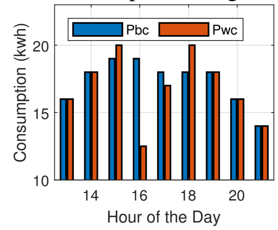
Fig. 2: The baseline energy consumption profile is presented with higher outdoor temperatures leading to increased cooling system energy consumption



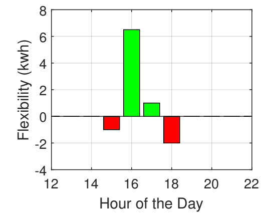

(a) With the TOU price plan, the customer peak consumption is 20kWh due to pre-cooling.



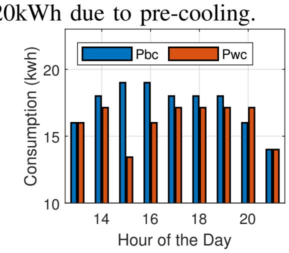

(b) TOU price plan customers can provide energy flexibility of 14 kWh.



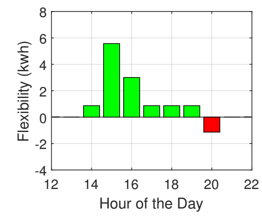

(c) With the EZ3 price plan, the customer peak consumption is 20kWh due to pre-cooling.




(d) EZ3 price plan customers can provide energy flexibility of 4.5 kWh.




(e) With the Residential demand price plan, the peak consumption is pegged at 17kWh to save cost.




(f) Residential demand price plan customers can provide energy flexibility of 10.9 kWh.

Fig. 3: Comparison of the energy flexibility potential among customers based on enrolled pricing structures.

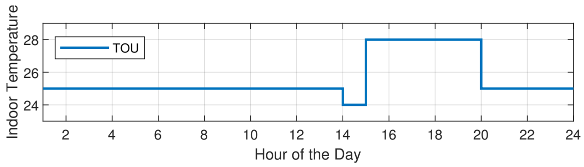
throughout the day, as shown in Fig. 2a. Consequently, energy consumption is calculated as the amount needed to sustain this indoor temperature, factoring in outdoor temperature conditions. The outdoor temperature data is from a typical hot summer day in Phoenix, Arizona, representing the forecasted conditions that influence the cooling system's energy usage. Fig. 2b presents the resulting base-case consumption profile. Understandably, hot outdoor conditions will require more energy consumption from the cooling system as it would run against a more significant temperature difference.

### *B. Flexibility Without Edge Resources*

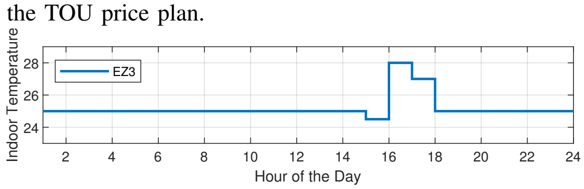
In this scenario, the outdoor temperature remains consistent with the base case for estimating flexibility. The assessment involves the cooling system's flexibility without incorporating additional grid edge resources. The model assumes that indoor temperature set point adjustments are permitted solely during peak hours. Consequently, the indoor temperature must align with the base case scenario, set at 25°C, outside peak pricing hours. Moreover, comfort criteria are introduced, stipulating that the indoor temperature must not deviate by more than ±3°C at any given time and that the temperature change between two periods must not exceed 5°C. Optimized and controlled through the flexibility approach, the resulting energy consumption profile is compared with the base case consumption profile for each pricing structure. Additionally, evaluation is conducted on the resulting indoor temperature.

The optimized consumption pattern of a customer under the TOU price strategy is shown in Fig. 3a. The room is pre-cooled immediately after the flexibility window opens during peak hours at 14:00, resulting in higher energy consumption. However, energy savings are implemented from 15:00 to 20:00 to reduce the total energy consumption cost. Following the peak hours, when electricity prices decrease, energy usage increases again to maintain the desired indoor temperature outside peak hours. Consequently, the customer follows a pattern of initially higher consumption, gradual reduction during peak hours, and subsequent increase to meet temperature constraints. The TOU price plan shows peak flexibility at 15:00, with a 7 kWh reduction in energy usage compared to the base case and an algebraic sum of 14 kWh of energy flexibility available. The hourly flexibility result is presented in Fig. 3b, and the indoor temperature profile is provided in Fig. 4a.

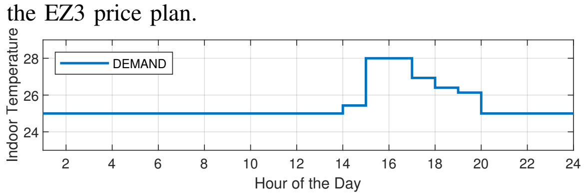
Next, with the EZ3 price strategy, the optimized consumption pattern of a customer is shown in Fig. 3c. The room is also pre-cooled immediately after the flexibility window opens during peak hours at 15:00, resulting in higher energy consumption. However, energy savings are implemented from 16:00 to 18:00 to reduce the total energy consumption cost. Following the peak hours, when electricity prices decrease, energy usage increases again to maintain the desired indoor




(a) Resulting indoor temperature profile for customers on the TOU price plan.




(b) Resulting indoor temperature profile for customers on the EZ3 price plan.




(c) Resulting indoor temperature profile for customers on the Residential demand price plan.

Fig. 4: Comparison of the indoor temperature profile obtained based on the optimal flexibility with the three pricing structures.

temperature outside peak hours. Therefore, the customer follows a similar pattern of initially consuming more than the base case, gradually reducing consumption during peak hours, and subsequently increasing consumption after the peak period to meet indoor temperature constraints. The EZ3 price plan shows peak flexibility at 16:00, with a 6.5 kWh reduction in energy usage compared to the base case and an algebraic sum of 4.5 kWh of energy flexibility available. The flexibility available to these customers is reduced compared to TOU customers due to a smaller flexibility window. In this case, only a 3-hour window is available compared to the 6-hour option offered by TOU pricing. The hourly flexibility result is presented in Fig. 3d, and the indoor temperature profile is provided in Fig. 4b.

The optimized consumption pattern of a customer under the residential demand price strategy is shown in Fig. 3e. The residential demand price strategy avoids pre-cooling, unlike the other two methods. This precaution is taken to prevent a surge in peak demand, which could result in higher prices under the demand price plan. Peak flexibility under this plan is observed at 15:00, with a 5.5 kWh reduction in energy usage compared to the base case. This results in an algebraic sum of 10.9 kWh of energy flexibility available. The flexibility available to these customers is not as high as that of TOU customers due to the restriction on pre-cooling. The hourly flexibility result is presented in Fig. 3f, and the indoor temperature profile is provided in Fig. 4c.

A comparison of energy flexibility in kilowatt-hours (kWh) across various pricing plans is presented in Table I. The total

TABLE I: Comparison of energy consumption and energy flexibility in kWh from different price plans

| **Model** | **TOU** | **EZ3** | **Demand** |
|---|---|---|---|
| Base case ($P_{bc}$) | 315 | 315 | 315 |
| Controlled ($P_{wc}$) | 301 | 310.5 | 304.1 |
| Flexibility ($\Delta P$) | 14 | 4.5 | 10.9 |

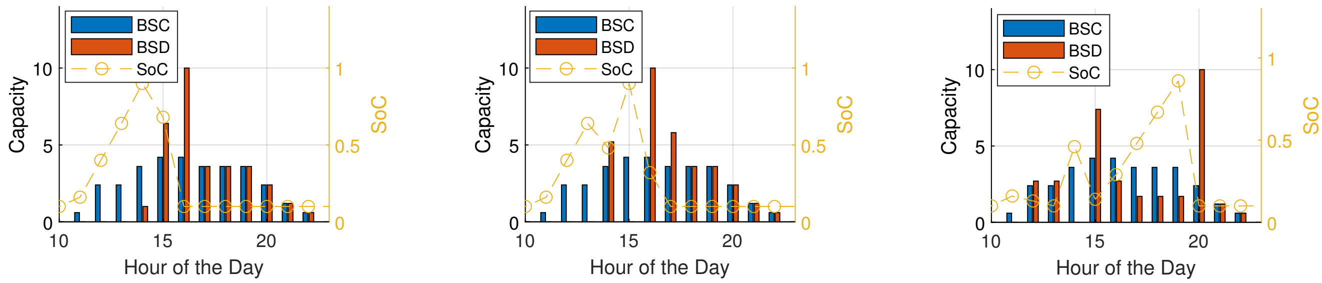
flexibility, denoted as $\Delta P$, is determined using (1) and (2). Fig. 3 illustrates the temporal flexibility pattern.

### C. Flexibility With Edge Resources

In this scenario, all the constraints in the previous scenario are maintained. However, we introduce the rooftop PV system and battery energy storage as grid-edge resources to provide more flexibility to the customer. The battery's state of charge is constrained to be between 0.1 and 0.9 at any time. The initial state of charge is set to 0.1. The battery charging or discharging capacity at any time step is constrained to be always less than or equal to the maximum battery capacity set to 10 kWh. Also, the PV system's output determines the battery's charging rate. Hence, the charging rate is high for periods of high solar irradiance, and for periods of low irradiance, the charging rate is low.

The optimized charging and discharging schedule for customers enrolled in the TOU price plan is presented in Fig. 5a. Notably, the battery reaches its peak discharge at 16:00, coinciding with peak pricing hours, effectively reducing customer energy costs. The consumption pattern is shown in Fig. 6a. Integrating grid-edge resources, such as PV and battery storage systems, significantly reduces the dependence on grid power during peak hours, providing more flexibility for system operators in managing peak load situations. After peak hours, energy consumption rises again to maintain indoor comfort levels, leveraging lower electricity prices. Primarily, the battery discharges during peak hours to reduce energy expenses. By adopting grid-edge resources, TOU customers can offer more flexibility during peak periods, boasting an aggregate energy flexibility of 46.4 kWh. The hourly flexibility result is presented in Fig. 6b, and the indoor temperature profile is provided in Fig. 7a.

Next, the optimized charging and discharging schedule for customers enrolled in the EZ3 price plan is presented in Fig. 5b. In this case, the battery also reaches its peak discharge at 16:00, coinciding with peak pricing hours and reducing customer energy costs. The consumption pattern is shown in Fig. 6c. By incorporating grid-edge resources, EZ3 customers can offer more flexibility during peak periods and boast an aggregate energy flexibility of 36.9 kWh. Even with grid edge resources, the flexibility available to these customers is lower than that of TOU customers due to a smaller flexibility window, which is only a 3-hour window compared to the 6-hour option offered by TOU pricing. The hourly flexibility result is presented in Fig. 6d, and the indoor temperature profile is provided in Fig. 7b.

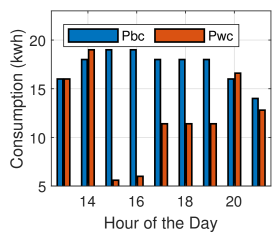



(a) The charging, discharging, and state of charge patterns of grid edge resources for TOU customers.

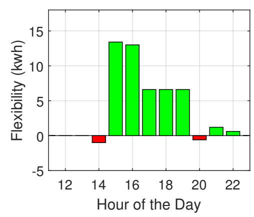
(b) The charging, discharging, and state of charge patterns of grid edge resources for EZ3 customers.

(c) The charging, discharging, and state of charge patterns of grid edge resources for residential demand plan customers.

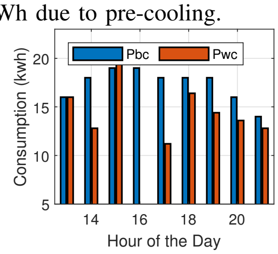
Fig. 5: The charging, discharging, and state of charge patterns of grid edge resources vary depending on the pricing structure for consumers.



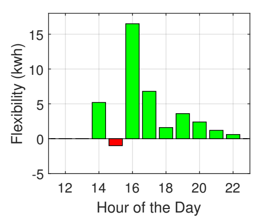

(a) With the EZ3 price plan, the customer peak consumption is 20 kWh due to pre-cooling.



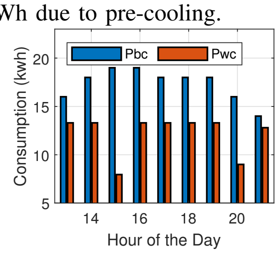

(b) TOU price plan customers can provide energy flexibility of 46.4 kWh.



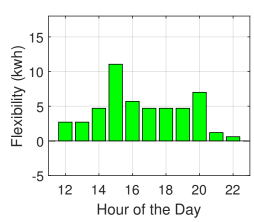

(c) With the EZ3 price plan, the customer peak consumption is 20 kWh due to pre-cooling.




(d) EZ3 price plan customers can provide energy flexibility of 36.9 kWh.

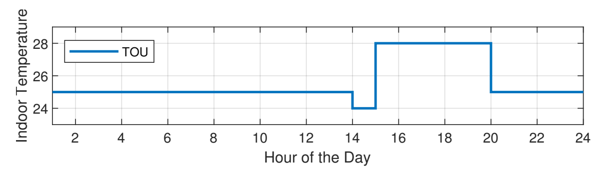



(e) With the Residential demand price plan, the peak consumption is reduced to 13 kWh.

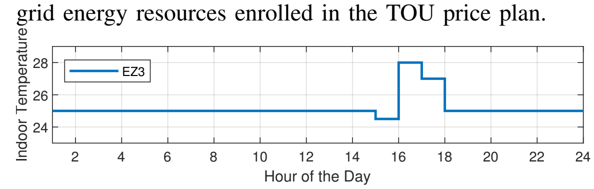



(f) Residential demand price plan customers can provide energy flexibility of 49.7 kWh.

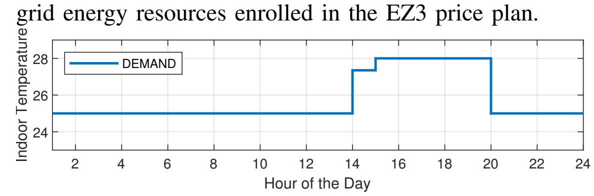
Fig. 6: Comparison of the energy flexibility potential among customers with grid edge resources based on enrolled pricing structures.




(a) Resulting indoor temperature profile for customers with grid energy resources enrolled in the TOU price plan.




(b) Resulting indoor temperature profile for customers with grid energy resources enrolled in the EZ3 price plan.




(c) Resulting indoor temperature profile for customers with grid energy resources enrolled in the residential demand price plan.

Fig. 7: Comparison of the indoor temperature profile obtained based on the optimal flexibility with grid edge resources on the three pricing structures.

Residential customers utilizing the demand-based pricing strategy observe significant advantages from leveraging grid-edge resources. The optimized charging and discharging pattern for demand-based pricing customers is shown in Fig. 5c. The battery reaches its peak discharge just after the peak pricing hours, around 20:00. This timing reflects the strategy of the residential demand price plan, which encourages spreading out energy consumption to prevent surges at any single point. The consumption pattern is detailed in Fig. 6e. Through this approach, customers reduce peak consumption from 17 kWh to 13 kWh, resulting in a notable decrease in energy costs, as peak consumption heavily affects price. Also, a total energy

TABLE II: Comparison of energy consumption and energy flexibility in kWh from different price plans after introducing grid edge resources

| Model | TOU | EZ3 | Demand |
|---|---|---|---|
| Base case ($P_{bc}$) | 315.0 | 315.0 | 315.0 |
| Controlled ($P_{wc}$) | 268.6 | 278.1 | 265.3 |
| Savings ($\Delta P$) | 46.4 | 36.9 | 49.7 |
| PV contribution | 32.4 | 32.4 | 32.4 |

flexibility of 49.7 kWh is available, more than that of TOU and EZ3 customers. The hourly flexibility is presented in Fig. 6f, and the indoor temperature profile is shown in Fig. 7c.

A comparison of energy flexibility in kilowatt-hours (kWh) across various pricing plans and highlighting the impact of integrating grid-edge resources is presented in Table II. The total flexibility, denoted as $\Delta P$, is determined using (1) and (2). Fig. 6 illustrates the temporal flexibility pattern. The base case consumption remains constant across all three pricing structures, as does the contribution from the PV system.

## IV. Conclusion

This study has examined optimizing and quantifying energy flexibility for a grid-interactive cooling system. The optimization is designed to help minimize the cost of energy utilization for the customer. Three different pricing plans have been considered, and the optimization results for each plan were compared against a base case (i.e., rule-based temperature control). Also, the effect of grid edge resources, including PV and battery energy storage, was evaluated to determine the flexibility level. The results show that the TOU pricing mechanism has the highest amount of flexibility. One limitation of this study is the simplicity of the developed models and the number of customer loads considered. Scaling up to include customer clusters or diverse customer types (residential, commercial, industrial) increases optimization complexity and computational demands. Future studies will incorporate customer clusters with different temperature settings, varying cooling device capacities, and the uncertainties of PVs, battery systems, and EVs. The objective is to examine and evaluate the implications and opportunities of spatial aggregation/disaggregation of diverse customer behaviors using graph-based estimation methods. Also, AI and edge computing techniques will be introduced to examine the stochastic nature of the outdoor temperature and the variability associated with PV supply.

## Acknowledgement

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Manuscript ID: 2024-IASAM24-0114

*"Customer Centric Price-Based Energy Flexibility Estimation for Thermostatically-Controlled Loads" by Joshua Olowolaju, Yuhan Du, Rakib Hossain, Javad Mohammadi, and Hanif Livani*

## Response to Decision Letter

Dear Editor,

The authors thank the editor and reviewers for the timely manuscript processing and for recommending our paper for acceptance for presentation at the IAS Annual Meeting. We have addressed all the comments raised by the reviewers and the editor in the paper and provided our responses. We submitted the revised manuscript and the following explanations in response to the reviewers' comments. We hope the editor and reviewers will find these explanations and modifications satisfactory.

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## Response from Authors to Reviewers' Responses to Questions

**Reviewer: 1**

1. This paper evaluates the energy flexibility of thermostatically controlled loads (TCLs) from a customer-centric pricing perspective. The evolving power grid landscape, driven by decarbonization efforts and diverse energy sources, increases grid complexity due to unpredictable and variable consumer demand influenced by weather, economic conditions, and preferences. Flexibly managed TCLs, like HVAC systems, can improve grid reliability and resilience by providing essential services such as peak load management. The study uses data from Phoenix, Arizona, to test three tariff models from SRP Electric Utility for energy and cost savings, formulating flexibility estimation as a linear optimization to minimize customer bills. The results underscore the value of grid edge resources for energy flexibility and the need for tailored pricing strategies for different customer segments. I think this paper merits a publication in this journal, with the following concerns that require the authors to response:

**Response:** We want to thank the reviewer for recognizing the contribution of our paper.

2. The dynamic thermal rating (DTR) system has been shown to enhance the rating of existing lines by 30-50%, with the latter being possible in desirable weather conditions. In addition, the DTR system has also demonstrated that it can achieve the said benefit with lower costs and shorter lead time as compared to other equivalent methods. Due to this the DTR system has been deployed before to enhance grid reliability in [“Network topology optimisation based on dynamic thermal rating and battery storage systems for improved wind penetration and reliability”, Applied Energy] and [“Optimisation of generation unit commitment and network

topology with the dynamic thermal rating system considering N-1 reliability", Electric Power Systems Research], as well as, to increase RES and EV penetrations in ["Optimal Dispatching for AC/DC Hybrid Distribution Systems With Electric Vehicles: Application of Cloud-Edge-Device Cooperation", IEEE Transactions on Intelligent Transportation Systems], ["Hierarchical and distributed energy management framework for AC/DC hybrid distribution systems with massive dispatchable resources", Electric Power Systems Research], ["Two-Stage Optimal Dispatching of AC/DC Hybrid Active Distribution Systems Considering Network Flexibility", Journal of Modern Power Systems and Clean Energy]. Given the added advantage of the DTR system, it is more beneficial to implement the flexible system rather than the static line thermal rating (STR) system, as being implemented here in this paper. Hence, it is imperative that the authors additionally consider the DTR system in their proposed model which is currently lacking. Otherwise, the authors should highlight in depth the drawback of the proposed model in terms of the flexible rating and provide a proposal on how this can be performed as future studies.

**Response:** We appreciate the reviewer's comment. Since this study focuses on a single residential customer, the distribution system topology, including the dynamic thermal rating of the distribution line, has yet to be considered. Dynamic thermal ratings (DTR) become essential when a cluster of customers spread over a distance is considered. DTR helps incorporate changes in real-time weather conditions, such as wind speed, solar radiation, and ambient temperature, along the line.

The DTR system provides flexible current-carrying capacity for transmission lines, which can help mitigate system congestion caused by thermal limits. This flexibility is valuable in reducing the curtailment of renewable energy generation due to line capacity constraints. We plan to expand future studies to include different customer clusters, where considering the distribution system topology and incorporating flexible line ratings will be beneficial.

**Reviewer: 2**

1. This paper assesses the potential energy flexibility of thermostatically controlled loads from a customer-centric pricing perspective. The work is a good contribution in the field, but it could benefit from knowing the following related literature: Optimal tracking strategies for uncertain ensembles of thermostatically controlled loads. The relevance of this suggestion is not only to deal with thermostatically controlled loads (as this manuscript), but also to deal with optimal control (as this manuscript) and estimation of uncertainty (as this manuscript). Thus, the authors are free to judge if the suggestion is appropriate for being mentioned. Apart from this suggestion, I judge this work as a good contribution for IAS meeting, but the following minor comments arise

**Response:** We thank the reviewer for recognizing our paper's contribution and suggesting this relevant literature. We have worked with the relevant literature indicated by the reviewer to improve the introduction section. We also aim to expand the current work to include uncertainty estimation, as suggested by the reviewer, in future studies.

**Introduction paragraph updated to include suggested literature**

Several approaches for estimating energy flexibility have been explored in the literature. For instance, setpoint adjustments are utilized in [14] to measure flexibility in commercial and residential loads for demand response purposes. [15,16] employed data-driven approaches to assess energy flexibility potential in residential load users. [17] quantified flexibility in thermostatically controlled loads using scenario-based approaches derived from power flexibility distribution functions. In [18], a home energy management system with model predictive control is employed to quantify flexibility in residential buildings, formulating flexibility bands and dispatching resources upon request. Also, [19] implemented a distributed controller involving a central load aggregator and building-level controllers to coordinate thermostatically controlled loads. Furthermore, [20] examined the application of adaptive model-free optimal control strategies for thermostatically controlled loads. Despite these advancements, energy stakeholders continue to pursue methods for quantifying demand flexibility, given its growing significance in modern distribution grid operations [21].

[20] Coimbatore Anand and S. Baldi, "Optimal Tracking Strategies for Uncertain Ensembles of Thermostatically Controlled Loads," 2020 IEEE 16th International Conference on Control & Automation (ICCA), Singapore, 2020, pp. 901-906, doi: 10.1109/ICCA51439.2020.9264495.

2. The authors write that this paper estimates the inherent flexibility potential of HVAC systems of individual residential houses from a pricing standpoint, evaluating their suitability for demand response initiatives. However, based on equation (3) and related equations, I mostly see an optimization problem. I did not spot where the estimation is inside such optimization. This might be better highlighted

**Response:** We want to thank the reviewer for this comment. Energy flexibility involves coordinating energy usage with the power grid to maintain comfort while balancing supply and demand. Smart devices allow electricity customers to automatically shift high energy consumption to cheaper periods and reduce usage when the grid is stressed. Thus, flexibility entails optimizing energy use across the grid to adjust consumption patterns.

Energy flexibility performance can be measured using various performance indicators focusing on different aspects of flexibility. This work quantifies flexibility potential as the energy a customer can save by rescheduling appliance operations. This is measured as the difference between base-case consumption ($P_{bc}$) and controlled consumption ($P_{wc}$), as shown in (1) and (2).

$$\Delta P^t = P^t_{\text{bc}} - P^t_{\text{wc}} \quad \forall t \in \{1, 2, \ldots, 24\} \tag{1}$$

$$\text{Flex} = \Delta P = \sum_{t=1}^{24} \Delta P^t \quad \forall t \in \{1, 2, \ldots, 24\} \tag{2}$$

To maximize flexibility potential at each time step ($\Delta P^t$), we introduce an optimization problem to minimize controlled consumption ($P_{wc}$) while maintaining the desired comfort level. In (3), the goal is to minimize $P_{wc}$ and examining the associated costs based on different pricing structures.

$$\text{Minimize:} \quad C_{total} = \boldsymbol{\lambda} \cdot \mathbf{P}_{wc} \tag{3}$$

The second paragraph in subsection II-A has been modified to clarify and enhance the reader's understanding.

**Excerpt of the modified paragraph in Section II**

$P_{bc}$, the base case power consumption represents the typical energy usage during regular operations. This value is derived from historical data through regression or machine learning models trained on predictor variables like outdoor temperature, humidity, cloud cover, and other climate indicators. It serves as the expected energy consumption for an average residential customer at specific time intervals. $P_{wc}$, the power consumption with control reflects a customer's energy usage when employing a customer-centric control strategy to minimize energy expenses. This controlled consumption considers outdoor weather conditions, room temperature, room setpoint, electricity prices, and cooling system capacity. To maximize flexibility potential at each time step ($\Delta P^t$), we introduce an optimization problem to minimize controlled consumption ($P_{wc}$) while maintaining the desired comfort level. The goal is to minimize $P_{wc}$ and examine the associated costs based on different pricing structures. Therefore, the objective function is defined in (3) as minimizing the cost of energy consumption subject to the desired comfort level and cooling system requirement constraints.

3. Because the work is heavily based on optimization, the authors may consider providing the computational time for it

**Response:** We want to thank the reviewer for this comment. While computational time is essential in optimization problems, this study focuses on a single residential customer, resulting in minimal computational demands that have not been considered. A single residential customer has minimal load and comfort level requirements, leading to very low computational needs. However, scaling up this optimization problem would require more computational time, which must be addressed.

For example, considering a cluster of residential customers introduces varying individual needs, thereby increasing optimization requirements and computational demands. Similarly, analyzing a distribution feeder with diverse customer types—residential, commercial, and industrial—would necessitate more complex optimization and longer computational times. Expanding the problem to account for uncertainties from PV and battery systems and outdoor weather conditions would further increase computational requirements.

In future research, we plan to include different customer clusters and address these uncertainties in the input variables. Then, we will address the computational time requirements. We have worked with this reviewer's comment to improve the conclusion section.

**Excerpt of the modified conclusion section**

One limitation of this study is the simplicity of the developed models and the number of customer loads considered. Scaling up to include customer clusters or diverse customer types (residential, commercial, industrial) increases optimization complexity and computational demands. Future studies will incorporate customer clusters with different temperature settings, varying cooling device capacities, and the uncertainties of PVs, battery systems, and EVs. The objective is to examine and evaluate the implications and opportunities of spatial aggregation/disaggregation of diverse customer behaviors using graph-based estimation methods. Also, AI and edge computing techniques will be introduced to examine the stochastic nature of the outdoor temperature and the variability associated with PV supply.

4. The authors write that using data from Phoenix, Arizona, three tariff models from SRP Electric Utility are tested for energy and cost savings. Maybe I missed it, but it is not clear if such data are available online or not. Apart from this, it is appreciated that the work is based on real data and I confirm that this work is a good contribution for IAS meeting.

**Response:** We want to thank the reviewer for this comment. The pricing models used in this study are from the SRP Electric Utility, Phoenix, Arizona. The data is available online and has been cited as [24].

[24] [Online]. Available: https://www.srpnet.com/price-plans/residentialelectric/compare-plans