Method for evaluating fairness of electricity tariffs with regard to income level of residential buildings

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HIGHLIGHTS

- Proposed an electricity pricing fairness evaluation method regarding income level.
- Demonstrated method to create income-conscious household energy models.
- Integrated diverse residential household models into co-simulation.
- Block tariffs, Time of Use, and Real-Time Pricing plans were considered.

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ABSTRACT

Modern advancements in energy technology, such as smart meters and renewable power generation, have contributed to the increasing penetration of time-variable electricity pricing plans. Under such plans, consumers experience a higher financial burden for consuming electricity when overall demand is high. Lower-income households may be disproportionately burdened by the transition to time-variable pricing because they tend to have less efficient homes and appliances, which may necessitate greater overall electricity consumption, especially during peak times. The goal of this work is to create a broadly applicable framework for evaluating the fairness of utility pricing plans. The proposed slope analysis method examines the distribution of a fairness metric across income levels in order to determine the level of fairness exhibited by a pricing plan. This work utilizes three fairness metrics, which are based on total household electricity bill and income, as a proof-of-concept for the slope analysis method and assesses their viability for fairness research. The proposed method also utilizes household energy models to represent various income levels for any location with sufficient data. The framework is evaluated using simulated households across 5 income levels and 3 climate zones in the United States. Fairness metrics are applied to the utility bills calculated under Real-Time Pricing and existing tariffs offered at each location. The proposed fairness evaluation method provides a quantitative measure of fairness and is broadly applicable across location and pricing plans. The metric based on the change in percentage of income spent on utilities considers the relative financial burden on households, which results in the slope analysis method outputting conclusive, accurate fairness determinations more often than the other examined metrics. The results demonstrate disparity in energy affordability, and the proposed slope analysis and model simulation methods provide a readily transferable testbed to evaluate energy policy equity.

Abbreviations: ATUS-CPS, American Time Use Survey – Current Population Survey; CA, California; CPS, Cyber-Physical Systems; DBT, Decreasing Block Tariff; D. C., District of Columbia; EIA, US Energy Information Administration; HVAC, Heating, Ventilation, and Air Conditioning; IBT, Increasing Block Tariff; IECC, International Climate Conservation Code; kWh, Kilowatt-hour; PIU, Percent of Income Spent on Utilities; ΔPIU, Change in Percent of Income Spent on Utilities; RECS, Residential Energy Consumption Survey; RES, Renewable Energy Sources; RPP, Regional Price Parity; RTP, Real-Time Pricing; SCB, Savings Compared to Baseline; TOU, Time of Use; TX, Texas; UCEF, Universal CPS Environment for Federation; US, United States; USD, United States Dollar.

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1. Introduction

Time-variable electricity pricing plans have become more prevalent due to advancements in energy technology, such as smart meters, renewable energy sources (RES), and transactive energy markets. However, such pricing plans may not fairly impact households across all income levels, as lower-income households tend to live in houses with inefficient structure and appliances [1–4]. Moreover, lower-income households are more likely to rely on electricity for heating and cooking [5,6]. Inefficiencies and greater reliance on electricity increase total electricity consumption and necessitate more consumption during peak price hours, compounding monetary penalties from peak demand pricing [5,6]. Therefore, it is imperative to investigate the fairness of utility pricing in order to guide future energy policy. The objective of this work is to propose a method for fairness evaluation and household model simulation, which can be used in conjunction with each other to perform such an investigation.

This work specifically considers consumer and group fairness, as described by Ekstrand et al. [7], with regard to household income level. There are several reasons for using income level to evaluate electricity pricing fairness, as opposed to considering other types of marginalization. First, there is evidence to conclude a relationship between income, energy efficiency, and energy consumption patterns [1–6]. Second, the social inequities experienced by various marginalized groups often manifest as disproportionate economic burden, particularly in the energy sector. For example, in the US, black and rural households on average spend about 4% and 6% more on utilities, respectively, than the national average [8]. There is also evidence that households marginalized because of race, education, and/or housing tenure receive fewer benefits from each unit of energy purchased [9]. Finally, income is easily quantifiable and applicable to most groups. Future research could weigh the various forms of marginalization for different communities; however, considering the scope of this work, income level is currently a pragmatic measure for evaluating electricity pricing fairness. Specifically, pricing is considered "fair" if it reduces disproportionate costs or burdens on lower income levels. This definition of fairness aligns with other energy fairness research and public perception [10].

Previous studies have examined the income-based fairness of traditional and time-variable electricity pricing plans. Traditional plans are typically based solely on consumption volume. Three traditional plans frequently considered by studies are: flat-rate, which maintains a constant price per kWh; Increasing Block Tariff (IBT), which increases price in steps for increasing brackets of consumption; and Decreasing Block Tariff (DBT), which decreases price in steps as consumption increases [11]. Time-variable plans change the price of electricity based on the time of consumption to reflect variation in electricity generation costs, availability of supply, and level of demand. Time-variable pricing can be implemented in various ways, though many of them can be described by one of two categories: Real-Time Pricing (RTP), which bases price on the current wholesale market price of electricity, or Time of Use pricing (TOU), which increases the price during preset hours determined from historical high demand.

Fairness researchers have reached conflicting conclusions pertaining to the fairness of the aforementioned pricing plans. In particular, consensus has not been reached about whether certain income levels are disproportionately harmed by switching to various pricing plans. Borenstein [12,13], Pacudan and Hamdan [14], and Ansarin et al. [15] examined traditional pricing plans. Borenstein found that switching from flat-rate to IBT redistributed wealth from the highest income level to the lower income levels [12,13]. Pacudan and Hamdan corroborated that IBT benefits lower-income households, as switching from DBT to IBT shielded them from subsequent price increases and pushed the burden onto high-income households [14]. However, Ansarin et al. found that implementing IBT caused wealth to be redistributed from RES non-owners to owners [15]. This result indicates that IBT is disadvantageous for lower-income households, as RES owners are typically of higher income [15,16]. Solar uptake data from 2018 shows that only 15% of solar adopters in the US had an income <80% of their respective area median income [17].

Disagreement about fairness is also present in research pertaining to time-variable pricing. Horowitz and Lave [18] switched customers from flat-rate pricing to RTP and found that lower-income households disproportionately experienced an increase in electricity cost. On the contrary, Burger et al. [19] performed the same pricing plan transition, but instead found that expenses decreased for low-income households. Further, Ansarin et al. [15] found that switching to RTP or TOU neither benefitted nor harmed any income level disproportionately. Simshauser and Downer [3] opposed this conclusion, as they switched customers from flat-rate pricing to TOU pricing and found that the majority of customers who experienced savings on electricity bills were low-income.

The discrepancies between fairness conclusions are likely due, in part, to researchers studying data from different locations. The studies examining traditional plans were based in Brunei [14], California [12,13], and Texas [15]; time-variable research was based in Illinois [18,19], Texas [15], and Victoria, Australia [3]. Because studies applying the same pricing plans to different locations come to conflicting results, there is evidence that electricity pricing fairness is dependent on location. Therefore, a fairness determination method needs to be broadly applicable so research can be performed for the location of interest. However, some studies come to conflicting conclusions about the fairness of a pricing plan in the same location. For example, Horowitz and Lave [18] and Burger et al. [19] both base their studies in Illinois yet come to conflicting conclusions about the fairness of transitioning from flat-rate pricing to RTP. As such, location cannot be the only reason for the lack of consensus amongst researchers.

Fairness researchers also employ different methods to evaluate fairness, particularly in the metrics used. Values used to quantify fairness include: the absolute cost of electricity [3,12,13], percent change in bill across different tariffs [12,13,16], ratio of electricity cost and income [14], electricity cost compared to customers' willingness to pay (i.e. consumer surplus) [14,15,19], and cross-subsidization, where some consumers overpay for electricity and effectively subsidize others' consumption [3,15,16,19]. Research has gone into determining which metrics best capture fairness in electricity pricing. Zaki and Hamdi [20] and Aurangzeb [21] argue that the ratio of cost to consumption volume is the most critical factor in determining whether the effects of a pricing plan are considered fair. Neuteleers et al. [22] proposes that the ratio of cost to household income should be a major fairness consideration to ensure that bills are within customers' ability to pay. Other researchers instead focus on minimizing cross-subsidies as much as possible [22–24]. If cross-subsidies are equal to zero, every consumer pays the exact cost of providing them with electricity. Finally, Ansarin et al. [23] provides general advice such as observing broader geographic regions, increasing time-granularity when studying time-variable tariffs, and evaluating against multiple tariffs.

Not enough evidence is available to indicate which metric best quantifies fairness. Additionally, some of the aforementioned metrics are likely to contradict each other, as some focus on grid health while others focus on customer burden. For example, a fairness metric which prefers penalization of larger consumption, as in [21], will likely conflict with a metric based on the ratio of cost to household income, as in [22], since household income is not necessarily proportional to consumption volume [1–6,11,12]. Furthermore, the metrics are not inherently linked to a fairness determination. In other words, the value of the metrics needs to be interpreted by the user as "fair" or "unfair," which may be a difficult distinction if results are ambiguous and is an entrypoint for personal bias. Finally, some metrics may not be practical to implement. Ansarin et al. [23] concedes that cross-subsidization data may be impossible to gather, as it requires determining the exact cost of providing electricity to each consumer. These limitations create the need for a metric which captures important aspects of fairness, outputs direct and consistent fairness determinations, and is practically implemented.

Finally, fairness researchers' distinctions of “low-income” households vary widely. For example, some classify based on absolute value of income in the form of brackets [12,13,19], while others consider whether households receive energy subsidies or bill assistance [3,18]. Neither method adequately considers all the factors which determine a household's income level. Monetary value of income does not account for factors which influence the cost of living a household faces. On the other hand, basing the classification on billing aid only includes households that apply; it does not consider those struggling with bills despite not qualifying for aid, known as a “cliff effect” [2]. This paper accounts for location and household size in income level determination utilizing a method developed by the presenting authors in Covington et al. [25] (in press).

This paper proposes a method that addresses the need for a practical electricity pricing fairness determination method which can be applied to any location. The proposed slope analysis method determines the level of fairness exhibited by pricing plans based on the distribution of a fairness metric values across income levels. The performance of three metrics in determining the level of fairness is evaluated. The fairness metrics utilize readily available data to remove the practical barriers associated with existing metrics, such as cross-subsidization, and involve the 1) change in electricity bill after switching pricing plans 2) ratio of electricity cost and household income, and 3) change in the ratio of electricity cost and household income after switching tariffs. The efficacy, benefits, and drawbacks of each metric are evaluated by applying them to electricity bills calculated from simulated household consumption and various pricing plans. Note that electricity bills under time-variable plans are dependent not only on consumption volume, but also on the time at which households use electricity. When combined with the proposed slope analysis method, an effective metric will quantify the net effect of different pricing plans on households in each income level and provide a conclusive determination of whether the pricing is fair. As this analysis is specifically for residential energy consumption, the ideal metric will also allow for adjustments in utility company revenue from the residential sector, such that an equitable discount or rate increase could be applied to all households.

This paper also proposes a novel simulation technique which combines model generation and co-simulation methods developed in prior works by the presenting authors. The automated method for generating household energy models of varying income level and location was established in Covington et al. [25] (in press). Models are developed stochastically using survey data, which is sorted by respondent income level and location. The co-simulation framework utilized for advanced HVAC control was developed in Woo-Shem et al. [26]. Integration of model generation and co-simulation enables simulation of a wide range of diverse households with more realistic HVAC behavior. Many previous fairness studies utilize meter data from real households [3,12–15,18,19]. Utilizing simulations removes the need to gather data from physical households, which makes testing diverse scenarios faster, cheaper, and non-invasive while providing more control over variables such as time granularity and data disaggregation. This paper focuses on modeling and studying single-family homes because inhabitants are more likely to have immediate control of their energy consumption and directly pay utility bills. This simplifies the modeling problem and likely increases the accuracy of survey responses pertaining to energy consumption, which are the basis for the models.

When studying the effects of different utility pricing plans, an important factor to consider is the demand elasticity of residential households. This paper assumes that households exhibit negligible demand elasticity to time-variable utility rate, which is supported by existing literature [12,13,23,27–29]. Ito [27] and Li et al. [28] analyzed electricity billing records from across the US and found that short-term demand elasticity is not statistically significant when compared to long-term average price elasticity. In effect, people base their consumption behavior on aggregate markers of cost, such as monthly bills, instead of current fluctuations in price. Borenstein [12,13] and Ansarin et al. [23] found that incorporating demand response into their models had little effect on fairness results. Hobman et al. [29] present psychological reasons for the lack of demand response such as lack of education, proclivity for the status quo, decision avoidance, and preference for instant gratification. Furthermore, the presenting authors found that optimizing residential HVAC to minimize cost under typical US time-variable pricing plans was not as effective at decreasing utility bills as other control strategies, such as adjusting the thermostat based on outdoor temperature or occupancy [26]. It follows that there is generally not enough incentive for households to adjust their HVAC to fluctuating prices when other control methods are simpler and save more money. This conclusion can be applied to the other residential end-uses of energy since the HVAC system makes up the majority of household energy consumption. Based on this evidence, and an overall lack of data detailing the demand response behaviors of different demographics, inelastic demand is assumed for the utilized household energy models.

In summary, this paper proposes a broadly applicable method for evaluating the fairness of electricity pricing plans. A quantitative evaluation of fairness is performed by plotting average household income against fairness metric values and analyzing the slope of the linear trend line. Three fairness metrics are tested with electricity bills from households of various income level in 3 US climate zones. The plans considered are flat-rate, block tariffs, TOU, and RTP because of their prevalence in current billing strategy and application to future billing, such as within a transactive energy market. Testing of the metrics is performed using the EnergyPlus [30] building energy simulator, with co-simulation for advanced HVAC control. Models are demand inelastic and generated stochastically using probability distributions unique to the household's location and income level. Probability distributions used for generating the testbed models were gathered from national-level surveys: the Residential Energy Consumption Survey (RECS) [31] and the American Time Use Survey-Current Population Survey (ATUS-CPS) [32]. Ultimately, the aim of this paper is to provide a proof-of-concept for the proposed fairness evaluation method, which can be applied to current or future energy policy.

2. Terminology and definitions

This section defines the terms used in the analysis, the presented fairness metrics, and the slope analysis method. Terms such as “income level” and “climate zone” may be ambiguous because they are used colloquially and are not consistently defined in literature. There may also be ambiguity in the naming and implications of pricing plans since conventions vary by location. Finally, the fairness metrics and slope analysis method are detailed here, since they are the main contribution of this paper. Discussion on applying and evaluating the method is found in Section 4.

2.1. Income level

The Pew Research Center [33] provides a quantitative definition for five US household income levels: low, low-middle, middle, high-middle, and high. A household is placed in a particular category based on a comparison between their annual income and the US median value. “Low” is considered <50% of the median income, “low-middle” is 50–66%, “middle” is 66–200%, “high-middle” 201–300%, and “high” is 300%. This definition offers a base categorization system for income level but is inadequate without additional consideration of the factors which influence household cost of living, including location and number of members.

The cost of living varies depending on location; a household located in a more expensive area pays higher costs to maintain the same standard of living as an identical household living in a less expensive area. The Regional Price Parity (RPP) is a metric for how relatively expensive living costs are in a certain area, expressed as a percentage of the average national price of goods and services. RPPs are provided for US states as well as specific metropolitan areas by the US Bureau of Economic Analysis [34]. The purchasing power of one United States Dollar (USD) can be adjusted to be in terms of the national average using the RPP. Therefore, income level thresholds can be normalized to match the cost of living in each location.

Household size is also crucial when determining income level. Maintaining a household with more members generates more costs than one with fewer members. To account for this, location-adjusted household income is compared to the national median income of households of the same size. Then income level is determined based on the aforementioned ratios provided by the Pew Research Center.

The presented method of determining household income level is quantitative, offers strict delineations between levels, and considers how households are affected differently by the same monetary value of income. Fig. 1 offers a visualization and summary of how income level is determined.

Note that although location and household size are major factors in household expenses, they may not be entirely sufficient for determining cost of living. A wide range of factors may be responsible for influencing cost of living and energy affordability, especially when considering characteristics of different locations. Researchers have the option to augment this income level determination method with additional factors. Household location and size were selected as the factors for this proof-of-concept for the proposed fairness evaluation method.

2.2. *Climate zone*

Climate zone is the main determining factor of thermal regulation needs, as HVAC and water heating comprises 77.4% of total US residential energy consumption [35]. Climate also plays a role in determining house structure and certain installed equipment, such as HVAC systems. Therefore, there are likely to be differences in how electricity pricing affects bills in different climates.

This paper's definition of climate zone is based on a modified version of the International Climate Conservation Code (IECC) definition [36]. Each county in the US is assigned a climate zone, denoted with a letter and number. The 19 zones considered by the IECC range from 0 A (extremely hot humid) to 8 (subarctic/arctic). The RECS [31] combines some IECC zones such that fewer climate zones encompass the country. This paper uses the same climate zone definitions as the RECS, which includes 11 climate zones.

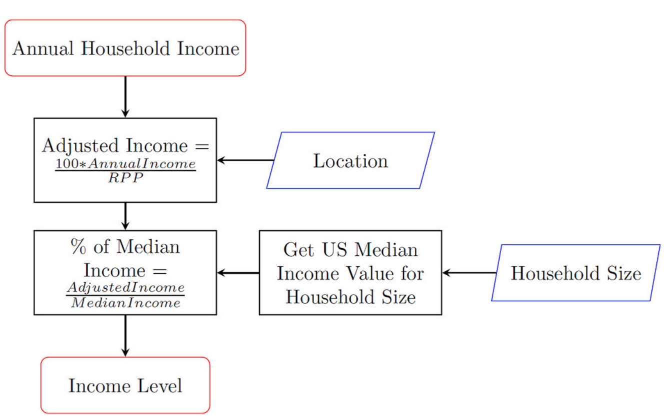

Fig. 1. Flow chart of household income level determination. The process begins with the monetary value of the gross annual household income. Gross income is considered because it is the income value provided by the surveys which were utilized as a data source (Section 3.4). This value then gets adjusted based on the relative cost of living in their area, which is quantified by the Regional Price Parity (RPP). Finally, the location-adjusted income value is compared to the US median income of households with the same number of members. Based on the ratio of location-adjusted and median income, a household is determined to be either low, low-middle, middle, middle-upper, or upper income.

Three climate zones were considered as a sample for the fairness analysis: 1 A-2 A (Hot Humid), 3C (Warm Marine), and 4 A (Mixed Humid). These zones were selected because they are representative of a wide range of climate conditions across the continental US. Metropolitan areas are chosen to represent each climate zone for the purposes of collecting weather data and relevant electric tariffs. The cities chosen to represent zones 1 A-2 A, 3C, and 4 A are Houston, TX, San Jose, CA, and Washington, D.C. respectively.

2.3. *Electricity pricing models*

Five pricing models are considered for the fairness analysis: flat-rate, IBT, DBT, TOU, and RTP. The flat-rate model assumes a single price per kilowatt-hour (kWh) of electricity regardless of time or total amount purchased. Block tariffs change the price per additional kilowatt-hour as customers reach certain tiers or "blocks" of total consumption during a billing period. The price of the electricity used below a given threshold is not affected when customers surpass that threshold. As customers surpass thresholds, IBT and DBT increase and decrease the price per kWh, respectively. To show the effects of changing to time-variable pricing models, either flat-rate or IBT was used as a baseline, depending on the plans offered by utility companies in the area.

TOU and RTP are time-variable plans. Under TOU pricing, there are time periods with higher and lower pricing according to a predetermined regular schedule. RTP has been offered by some utility companies in recent years and is projected to become more prevalent with the increasing adoption of smart electricity meters [37] and development of transactive energy markets. The RTP model based on a function of wholesale price has been used previously by the team of presenting authors [26] and has been implemented by some utility companies [38,39]. For this work, the wholesale price of electricity is obtained from the independent system operator in each location. To convert the wholesale price to a consumer price, The time-average RTP over the simulation period is the same as the average price under the baseline pricing system. When IBT is the baseline, the average cost per kilowatt-hour for RTP is the rate at which the majority of total energy consumption is charged. Example visualizations of RTP and TOU are shown in Fig. 2.

For each location, prices are chosen to match the actual retail prices charged to consumers for the flat, IBT, and TOU pricing plans during select time periods in 2022, the most recent year with data available at time of publication. Different utility companies offer a variety of rate plans, and schedules for time-variable pricing are specific to each location. Only RTP and plans that were available at the time of analysis are considered for each location. The flat-rate pricing model is used as a baseline if available in a location, otherwise IBT is used as a baseline. The pricing systems used in each of the simulated locations are shown in Table 1. Prices are different in winter and summer in San Jose, CA to reflect seasonal differences in supply and demand [42,43], however other locations use the same pricing for the entire year. In Houston, TX, multiple utility companies offer competing pricing plans and prices from one utility company were used to demonstrate the methods developed in this work.

2.4. *Fairness metrics & slope analysis*

Fairness in this work is measured by equitable relative or absolute financial burden across income levels. Three measures of fairness are used in this analysis to quantify the effects of certain pricing plans. Savings Compared to Baseline (SCB) measures relative change in absolute cost using the percentage decrease in customer bills under each new pricing plan compared to the baseline pricing system. Therefore, a positive SCB indicates that the consumer saves money. The formula for calculating SCB is shown in Eq. 1. The cost of electricity bills is represented by C, with the subscript notating whether the cost is from the original baseline tariff or the newly applied tariff. SCB is based on the

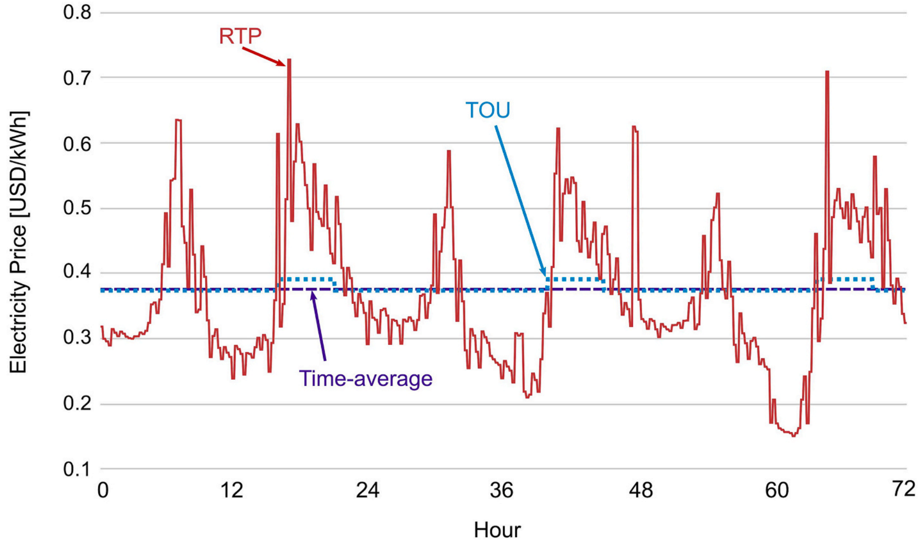

Fig. 2. Illustration of the Real-Time Pricing (RTP) for San Jose, CA during January 7–9. RTP is based on a function of the wholesale market. The average price of RTP is set to the baseline pricing system, shown as the "Time-average." Time granularity may vary between providers, but in all cases RTP value varies significantly throughout the day and is based on real-time data, as the name suggests. For comparison, the Time of Use (TOU) plan and the average price over time are shown. TOU plans raise prices during periods of historically high demand according to a regular schedule.

percent change in cost when switching from the baseline pricing system to a new tariff, similar to other difference-based metrics in existing literature [12,16].

$$SCB\,[\%] = \frac{C_{baseline} - C_{new}}{C_{baseline}} \cdot 100\% \tag{1}$$

Percentage of Income spent on Utilities (PIU) measures the relative burden of electricity bills on households, considering their income level. Because of their lower annual income, electricity bills are likely to be a larger burden on lower-income households than their higher-income counterparts. PIU is inspired by works that attempt to make all customers pay the same percentage of their total income or cap the total percentage of income that customers pay. Some countries classify households as "energy impoverished" if they spend more than a certain proportion of their income on energy; in the US this percentage is 6% [9]. In this study, the average annual household income is found from the 2015 RECS [31] for each income-climate classification. Then, the percentage of the income required to pay the utility bill is computed using Eq. 2, where C is the cost of electricity, and I is the monetary income during the time period of interest.

$$PIU\,[\%] = \frac{C}{I} \cdot 100\% \tag{2}$$

The Change in Percentage of Income spent on Utilities (ΔPIU) compares the PIU for a new pricing plan against the baseline price for that income level, as shown in Eq. 3. PIU_{new} is the PIU for a particular income level under a new tariff system, and $PIU_{baseline}$ is the PIU for the same income level under the baseline pricing. The objective of ΔPIU is to compare the increase or decrease in the burden on households caused by changing to a new pricing plan.

$$\Delta PIU\,[\%] = PIU_{new} - PIU_{baseline} \tag{3}$$

Each metric corresponds to a different contextualization of fairness. SCB quantifies fairness in terms of increasing absolute financial benefit as household income decreases. ΔPIU is used when fairness is classified by a more equitable electricity cost burden compared to previous tariff structures. For PIU, fairness is defined as having an equitable average electricity cost burden for all income levels. Note that both SCB and ΔPIU measure the fairness improvement by transitioning between tariffs, whereas PIU computes the fairness of a single tariff. While these metrics do not encompass every factor which can be considered in evaluating residential energy fairness, they set up an initial framework which may be built upon for the development of more complex metrics.

The proposed slope analysis method examines the relationship between fairness metric value and income level to calculate the level of fairness exhibited by a pricing scheme or transition between pricing schemes. For each income level, average metric value and household income are plotted against each other, and a linear trendline is fitted to the data. Depending on the metric used, either a positive or negative slope indicates fairness. However, it is necessary to also consider the uncertainty associated with calculating the trendline equation. Therefore, the slope and its standard deviation are used to perform a null hypothesis test finding the probability that the slope is truly "fair" (i.e. positive or negative, depending on the metric) and not due to random variation. If the resulting probability is close to 100%, the pricing plan – or transition between plans – can confidently be considered fair. Conversely, a probability close to 0% is a strong indication of unfairness. Uncertainty in the conclusion is quantified by the difference in the probability value and 100% or 0%, whichever is closest.

Whether a metric indicates fairness with a positive or negative slope is based on the aforementioned definition of fairness. For SCB, the slope is considered fair if it is less than or equal to 0, which indicates that either all income levels experience identical cost change or lower-income households gain the most savings. If the slope is positive, higher-income groups benefit at the expense of lower-income groups, which is an unfair outcome. Conversely, when considering PIU and ΔPIU, a fair slope is greater than or equal to 0, which means that low-income households spend less of their income on bills and therefore benefit more than the other income levels.

3. Developing household models for simulation

It is crucial that simulated models represent both constant and time-variant characteristics realistically. A level of randomness must also be considered because broad variation exists in house structure and consumption characteristics across households, and behavior varies over time within even a single household. Section 3 provides an overview of the method used to generate diverse, realistic, and semi-random household energy consumption models. A more detailed description is provided by the presenting authors in Covington et al. [25] (in press).

Table 1
Electricity tariffs used in analysis. The types of plans offered by utility companies and operation schedules vary between locations. This analysis only considers plans offered in each location and the proposed Real-Time Pricing (RTP). Plans offered by utility companies include flat-rate, Decreasing Block Tariff (DBT), Time of Use (TOU), and Increasing Block Tariff (IBT). Note that for IBT and DBT, the energy consumption ranges shown are for the two-week simulation period. For Houston, TX, the TOU electricity cost is zero between certain hours as an incentive for load-shifting.

Location	Pricing Systems Used	Electricity Cost, January 1–14 [USD/kWh]	Electricity Cost, August 1–14 [USD/kWh]	Source
Consumption-Based Pricing Plans				
Houston, TX	Flat	0.1478	0.1478	Reliant [40]
	DBT	0.1503, 0 to 500 kWh	0.1503, 0 to 500 kWh	Reliant [40]
		0.1303, above 500 kWh	0.1303, above 500 kWh	
San Jose, CA	IBT	0.3147, 0 to 147 kWh	0.3147, 0 to 169 kWh	PG&E [42]
		0.3945, 147 to 587 kWh	0.3945, 169 to 677 kWh	
		0.4932, above 587 kWh	0.4932, above 677 kWh	
Washington, D.C.	IBT	0.0111, 0 to 15 kWh	0.0111, 0 to 15 kWh	PEPCO [45]
		0.0944, 15 to 200 kWh	0.0944, 15 to 200 kWh	
		0.1032, above 200 kWh	0.1032, above 200 kWh	
Time-Variable Pricing Plans				
Houston, TX	TOU	0.3065, 6 am – 8 pm	0.3065, 6 am – 8 pm	Reliant [40]
		0.0000, 8 pm – 6 am	0.0000, 8 pm – 6 am	
	RTP	Time-average to 0.1478	Time-average to 0.1478	ERCOT [41]
		Years 2018–2022	Years 2018–2022	
San Jose, CA	TOU	0.3911, 4 pm – 9 pm	0.4881, 4 pm – 9 pm	PG&E [43]
		0.3737, otherwise	0.4247, otherwise	
	RTP	Time-average to 0.3755	Time-average to 0.4379	CAISO [44]
		Years 2019–2022	Years 2019–2022	
Washington, D.C.	RTP	Time-average to 0.0944	Time-average to 0.0944	PJM
		Years 2021, 2022	Years 2021, 2022	[46]

3.1. Co-simulation software

Household models are simulated using EnergyPlus [30], a building energy simulation program which has inputs for structural information, ambient conditions, energy load profiles, and occupant behaviors. An algorithm (Section 3.2) stochastically selects household characteristics and writes them directly into an EnergyPlus file. HVAC control is performed in Java, connected by the co-simulation platform Universal CPS Environment for Federation (UCEF) [47]. EnergyPlus operates the HVAC system with variable power rates, which is not realistic for most buildings. The Java program controls the HVAC system with more realistic binary on/off cycling. The technique for co-simulating EnergyPlus and UCEF was developed and utilized by the team of presenting authors in Woo-Shem et al. [26] and Singer et al. [48]. All other aspects of the simulation are performed by EnergyPlus.

3.2. Characteristic selection algorithm

The model generation algorithm utilizes a stochastic method to select household characteristics before writing them into an EnergyPlus model file. Probability distributions (Section 3.4) for each characteristic category (Section 3.3) are used alongside random number generation to ensure that model characteristics follow realistic trends while also upholding randomness and diversity. The algorithm determines the expression of each household characteristic in succession. For clarification, an example of a "characteristic" is the "number of refrigerators in the house" with a possible expression of "2 refrigerators." Note that some characteristic categories are constant, while others are time-variant.

Constant characteristics are determined once during the model generation process and include house structure, occupant behaviors, and appliance stock. Time-variant characteristics include the start times of certain human-operated appliances. The days and times of appliance operation are determined before the simulation begins because it is assumed that residential short-term electricity demand is inelastic. Characteristics are determined utilizing random numbers generated between 0 and 1 with a Java method which generates pseudo-random numbers exhibiting a uniform distribution [49]. A random number is compared to the probability distribution of a particular characteristic expression. The expression whose probability range contains the random number will be selected. Fig. 3 is a visualization of the selection process.

3.3. Model characteristics considered by the algorithm

Characteristics with a large effect on residential energy consumption are selected as the focus of the model generation algorithm to decrease data collection requirements. The US Energy Information Administration (EIA) provides data on total residential US energy consumption, including the proportion breakdown of end-uses. From highest to lowest consumption, the end-use proportions are HVAC (56.1%), water heating (21.2%), major appliances (10.7%), "other" (6.4%), and lighting (5.6%) [35]. Household characteristics which heavily contribute to these end-uses are considered by the model generation algorithm. Other characteristics are kept as the default of the base household energy models provided by the Office of Energy Efficiency and Renewable Energy

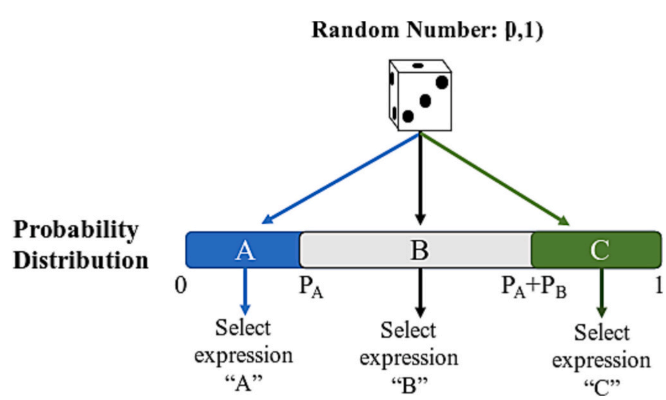

Fig. 3. Visualization of the characteristic expression selection method for generating household energy models. The probability distribution bar contains the probability of selecting a characteristic expression within a characteristic category, written as "P_i". As an example, a characteristic category could be "number of refrigerators in the house," and expressions could be "1," "2," or "3." Probabilities are gathered from national-level survey data. First, a random number is generated between 0 and 1. Then, the characteristic expression range which contains the random number will be selected. This process is repeated for each characteristic being modeled, and it is repeated for time-variable characteristics, such as the start times of appliances.

within the US Department of Energy [50]. An overview is provided with Fig. 4.

The HVAC consumption is largely dictated by house size, insulation level, windows, and thermostat settings, and heating fuel. These factors determine the thermal mass of the house, thermal leakage in/out of the house, and the amount of energy needed to reach a comfortable temperature range.

The energy consumption of the water heater is based on household hot water demand and the equipment's characteristics. Hot water demand is based on the size of the house, in particular the number of bedrooms and bathrooms. The energy factor of the water heater is determined by its fuel type, tank size, Energy Star classification, and age. The energy factor is an indicator for the efficiency of the water heater and how much energy it consumes to meet household demand.

The energy consumption of major household appliances (i.e. the refrigerator, oven, cooktop, dishwasher, clothes washer, and clothes dryer) is determined by their physical qualities and operation times. First, for each instance of the appliances, the algorithm selects physical characteristics relating to energy consumption. Next, operation times are determined as described in Section 3.2, except for the refrigerator which is assumed to follow the default schedule provided by the base models. Where applicable, the duration of each appliance run is determined stochastically. Lighting and "other" electric consumption are based on the wattage per floor area, which is stochastically selected. Both are maintained on the default base model schedule.

3.4. Probability distribution creation

Probability distributions for household characteristics ensure models follow real-life trends from their designated income level and climate zone while maintaining randomness and diversity. The data used to create the probability distributions was gathered from two surveys: the 2015 RECS [31] and the 2019 ATUS-CPS [32]. These versions of the surveys were selected because, at the time of the analysis, they were the most recently available version not affected by the COVID-19 pandemic. Note that the model generation method could utilize data from any time period, depending on the purpose of the research being conducted.

The RECS provides information regarding house structure, equipment/appliances present in the home, and time-invariant household behaviors. The ATUS-CPS provides daily activity diaries of respondents, which are used to gather probability distributions for the start time and day of the week of appliance operation. Both surveys provide socioeconomic and location data for each respondent, which allows survey responses to be sorted by income level and climate zone. Note that, after a multinomial chi-squared test, variation of appliance start time and day with climate zone was found to not be significant at a 99% significance level [25] (in press). After preprocessing the data, the ATUS-CPS contained about 23,000 entries and the RECS contained around 4500. Finally, the probability distributions were gathered for all model characteristics discussed in Section 3.3. For each income-climate classification, the number of selections of each characteristic expression was divided by the total number of responses for that characteristic category.

3.5. Validation of the model

Model validation is performed by comparing when, how, and how much energy is consumed between simulated and surveyed households. To collect data for validation, annual simulations were run for ten households per income level for US climate zones 1 A-2 A, 3C, and 4 A. The number of models used was justified by analyzing the moving average of household consumption within an income-climate classification. After 10 models were considered, average consumption remained within ±10% of the average of 1000 models.

Correlation analysis is used to determine the statistical similarity in the consumption patterns of simulated and surveyed households. Similarity is quantified by fitting the data with a linear trendline, where perfect similarity is indicated by a correlation coefficient (r) of 1, a slope of 1, and a y-intercept of 0. Note that the linear trendlines used in this work are constrained to pass through the origin, which offers several benefits. First, the constraint enhances the reliability of the test by deliberately inducing a worse-case scenario where the correlation is decreased due to a worse-fitting trendline. Secondly, the constraint simplifies the validation process by making the slope the sole parameter. Finally, forcing the line to pass through the origin aligns with domain knowledge of the model generation method, for it is impossible for simulated households to consume energy if none of the members of a survey group consume energy.

Null hypothesis tests are employed to quantitatively determine whether the observed values for r and slope are sufficiently close to 1, signifying the ideal case where the energy consumption of simulated and surveyed households match perfectly. The tests give the probability that a variable is truly equal to 1, with any observed deviation from 1 solely attributed to random variation in the data. For a 95% confidence level, a probability of <5% ($P < 0.05$) indicates that the variable truly differs from 1; otherwise, there is not sufficient evidence to reach this conclusion. For each case studied, two tests are performed: the r test and the slope test. The r test returns the probability (P_r) that uncorrelated data produces an r value greater than or equal to the observed value. For a 95% confidence level, the correlation is considered "highly significant" if P_r is <1% [51]. The slope test returns the probability (P_M) that the slope of the linear trendline is truly equal to 1, and any difference is solely due to random variation. If P_M is >5%, there is not enough evidence to conclude the slope differs from 1. Therefore, if P_r is <1% and P_M is >5%, then the data correlation is highly significant and the two

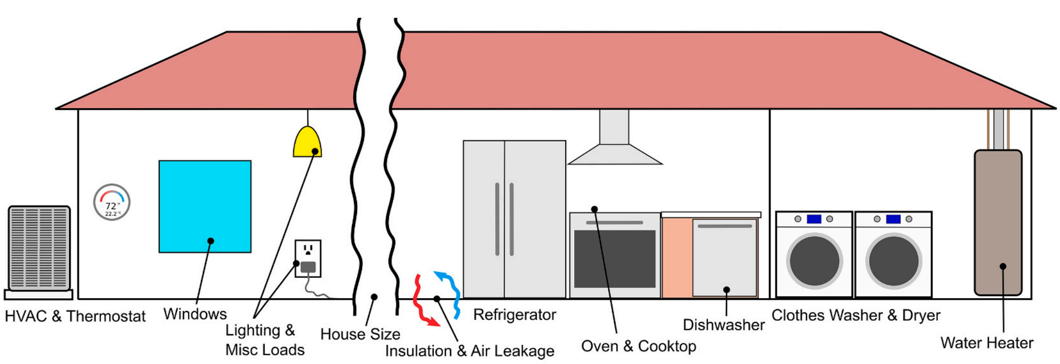

Fig. 4. Household characteristics that are determined by the proposed model generation algorithm. The model generation method focuses on these characteristics because they most affect household energy consumption. The operation times of the oven, cooktop, dishwasher, clothes washer, and clothes dryer vary throughout the simulation. Each start time is determined stochastically based on probability distributions before the simulation begins. The other characteristics remain constant throughout the simulation.

datasets cannot be proven as dissimilar.

Covington et al. [25] (in press) matches *when* time-variable appliances are being used for simulated versus surveyed households. The results are applicable to this study since the appliance operation times are independent of co-simulation control of the HVAC system. The start times of the time-variable appliances were sorted into time-steps and thousands of appliance runs were counted. For all income levels, the correlation is highly significant ($P_r < 1\%$) and there is no statistical evidence to suggest that appliance use patterns are different between simulated and surveyed households ($P_M > 5\%$).

This paper validates *how* energy is consumed by calculating the proportion of energy being consumed by the five major residential end-uses as presented in Section 3.3: HVAC, water heating, major appliances, lighting, and "other." Surveyed [31] and simulated households are sorted into their respective income-climate classification and then the energy consumption profiles of each household are broken down into the end-use categories. Consumption allocated to each end-use is summed across all households within an income-climate classification. For each end-use, the sum is divided by the total energy consumption of the income-climate classification, such that the sum of all end-use proportions is 1. Surveyed and simulated end-use proportions are plotted against each other, resulting in 75 data points because there are 5 income levels, 3 climate zones, and 5 end-uses considered. The correlation is highly significant ($P_r < 1\%$) and the end-use proportions cannot be proven dissimilar ($P_M > 5\%$). Therefore, simulated and surveyed households similarly allocate energy across the end-use categories.

Validating *how much* electricity simulated households use involves comparing the average total annual electricity consumption for simulated and surveyed [31] households in each income-climate classification. Because there are 5 income levels and 3 climate zones considered, there are 15 data points plotted for correlation analysis. The correlation of electricity consumption data is highly significant ($P_r < 1\%$) and the slope cannot be determined as different from 1 ($P_M > 5\%$). Therefore, there is no statistical evidence that simulated and surveyed households differ in total electricity consumption. The same conclusion is reached when comparing individual simulated household consumption to the average of their surveyed counterparts in the same income-climate classification.

3.6. Fairness metric evaluation simulation conditions

For each location, simulations were run for the first two weeks of January and August to compare the effects of various pricing plans during winter and summer, respectively. Different seasons were tested because electricity consumption profiles vary with the weather as thermal regulation needs change. Also, some utilities change electricity pricing plans depending on the season. Seasonal weather was implemented into the simulation with Typical Meteorological Year weather data, which is a representation of the median weather conditions across multiple years for each discrete time step. The weather data was obtained from the EnergyPlus website [52] for each location.

The simulations were performed using a 5-min timestep. The output includes household energy consumption for each 5-min interval of the simulation period. Electricity bills were calculated for the available tariff plans at each location as listed in Section 2.3 using the electricity consumption at each timestep. Fairness metrics were applied to the average bill for each income level. Analysis was performed on the linear trendline fitting average income of each income level plotted against the average metric values, as described in Section 2.4. Results are discussed in Section 4.

4. Results and discussion

This section demonstrates the performance of the proposed slope analysis method while examining the merits and limitations of the SCB, PIU, and ΔPIU metrics (Section 2.4). The fairness of switching to certain pricing plans is determined through analyzing the bills accrued during a two-week period by simulated households in San Jose, CA, Houston, TX, and Washington, DC. The pricing tariffs used are described in Section 2.3 and the simulation conditions are further detailed in Section 3.6. SCB is discussed first in Section 4.1, followed by PIU in Section 4.2 and ΔPIU in Section 4.3. Finally, Section 4.4 analyzes the level of fairness for each testing scenario.

4.1. Savings compared to baseline (SCB)

The SCB for the simulations and the average electricity consumption of homes in each income level are shown in Fig. 5. In most cases, the low- and low-mid- income households used more electricity compared to the high-income households, demonstrating the consequences of having less efficient homes and relying on electricity for more household functions. Additionally, SCB shows different patterns in each location and tariff, which will now be discussed in detail.

For Houston, TX, transitioning to DBT yields savings for customers who use more electricity in general, which tend to be lower-income households for the winter months and both low- and mid-high- income houses during the summer. During the summer, changing to TOU and RTP causes low-income households to suffer cost increases of 46.6% and 15.9%, respectively. Under these tariffs, electricity prices are higher when energy consumption tends to be higher, which includes the daytime hours when people tend to run air conditioning.

In the San Jose, CA simulations, the switch to TOU and RTP led to cost increases across all income levels. The cost increase with RTP was more severe, with the resulting SCB values being 5% to 10% greater than the TOU case. This is due to households being penalized for consuming electricity during times of high demand. For both TOU and RTP, SCB exhibits a negative slope, with the exception of a disproportionate cost increase for low-income households. During the winter, low-income households experience cost increases that are approximately 10% greater than low-mid-income and about the same as mid-high-income households. In the summer, the lowest-income level pays more than the low-mid-income group, though to a lesser extent.

The results for transitioning to RTP in Washington D.C. in the winter exhibit savings for all households and a gradual decrease in savings as income level increases. In the summer, total bills increase slightly for all customers, but no >1.8% for any given income level. However, low-mid- and middle-income houses have the largest increases.

SCB may be useful to measure the effect on utility company revenue when electricity costs increase or decrease across all residential customers. For example, SCB shows that all income levels pay at least 35% more by transitioning to certain pricing plans in Houston, TX or San Jose, CA. However, the critical limitation of SCB is that it does not consider how cost savings or increases affect households based on their budget.

4.2. Percent of income spent on utilities (PIU)

Results using the PIU metric to consider a household's ability to pay bills are shown in Fig. 6. Note that PIU considers only one pricing plan and not the difference between plans. In all cases simulated, high-income households pay <1.6% of their income in electricity bills, and low-income houses spend at least 6% of their income.

In Houston, TX, PIU decreases as income level increases, with a large difference between low- and low-mid-income households. In the winter, the largest change between the two income levels is 7.9% under TOU; in the summer the gap increases to 12.2%. Compared to the winter, PIU increases for all income levels in the summer, such that low-income households pay as much as 18.4% of their total income under TOU, and high-income homes spend 1.5%.

Households in San Jose, CA follow a similar trend, although the difference between low- and low-mid-income houses is relatively less extreme. In the winter, low-mid- and middle-income houses exhibit the

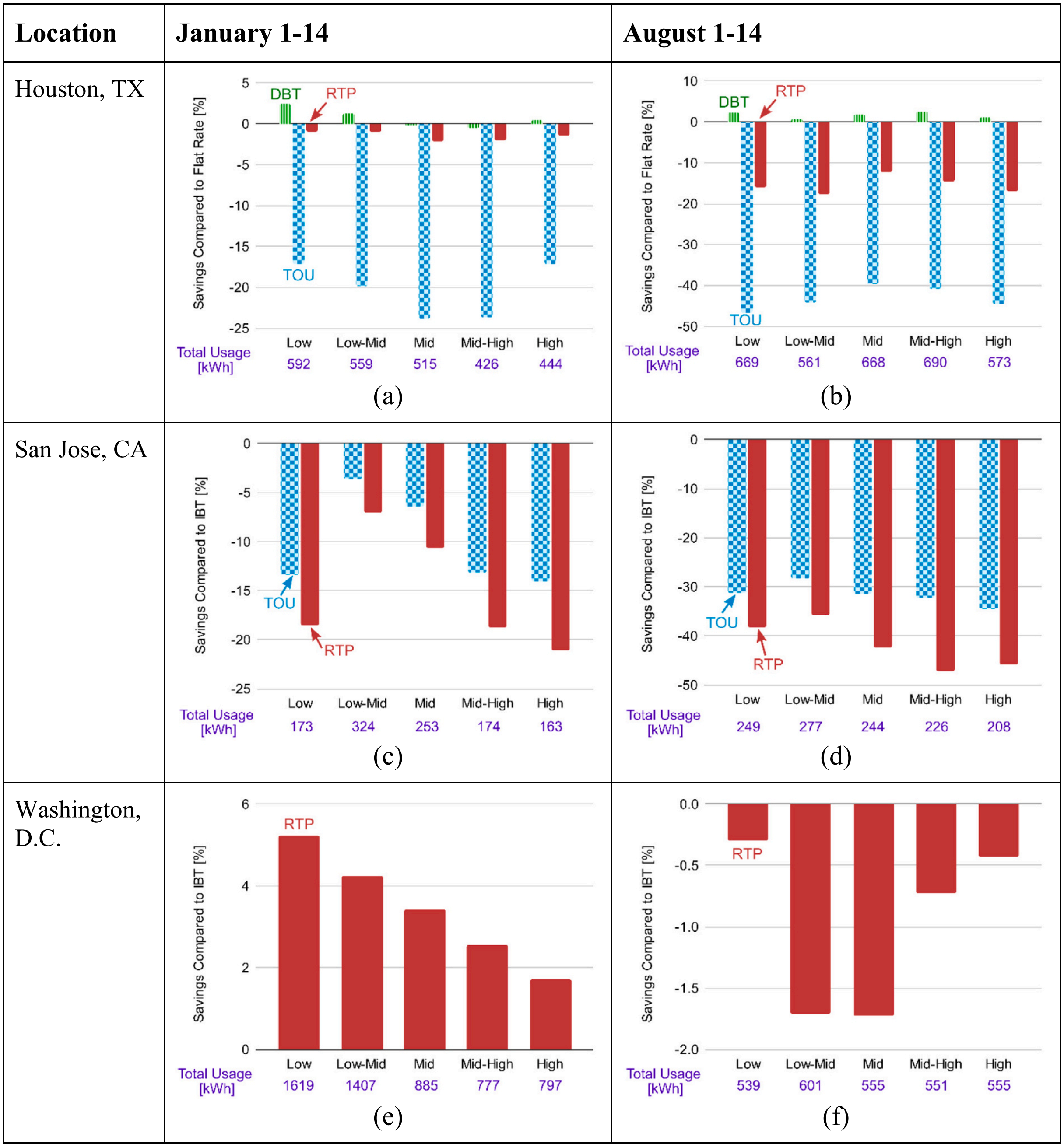

Fig. 5. Savings Compared to Baseline (SCB) of various pricing plans and the average total electricity consumption for each income level and location during a 2-week period. SCB values were calculated using the average electricity bill for each income level. Note that the income level axis is not to scale in the figures for presentation purposes, but slope analysis was performed with metric value plotted against the corresponding income level's average income value. SCB is a metric of fairness which measures percent change in electricity bill when switching between pricing plans. As such, a positive SCB indicates that households save money, whereas a negative SCB indicates that money is lost. Bills are calculated using the energy consumption data of simulated households. Pricing systems analyzed are RTP and those offered by the utility company in each location. The simplest pricing scheme offered by utility companies at each location is used as the baseline. Houston, TX uses flat-rate pricing as a baseline, where price per kWh remains constant. San Jose, CA and Washington, D.C. use Increasing Block Tariff (IBT), as a baseline, where price per kWh increases with increasing brackets of consumption. Each location is transitioned to other pricing plans offered, including Decreasing Block Tariff (DBT), Real-Time Pricing (RTP), and Time of Use (TOU). DBT decreases price per kWh with increasing consumption, RTP bases the price off of the real-time wholesale market, and TOU increases price during historical periods of high demand.

largest difference in PIU because of the comparatively high consumption by low-mid-income houses. During the summer, with RTP, low-income houses spend 12.3% of their income, whereas low-mid-income homes pay 6.6% and high-income households pay 1.1%.

PIU suggests that Washington, D.C. in the winter exhibits the most burdensome situation for low-income households. Under IBT, the PIU is 21.0% for low-income households, and RTP improves this to 19.9%. However, for middle-income the PIU is 2.9% and 2.8% under IBT and RTP respectively, and high-income the PIU is about 1.0% for both tariffs. In the summer, IBT and RTP have PIU values within 0.05% of each other; the gap between low- and high-income decreases to 5.8%; low-income homes have a PIU of 6.5%; and high-income houses have a PIU of 0.7%.

PIU emphasizes how differences in income make utility bills more burdensome for low-income households. This metric can measure the fairness of existing tariffs if the goal is to have households within each income bracket to, on average, contribute an equal share of their net

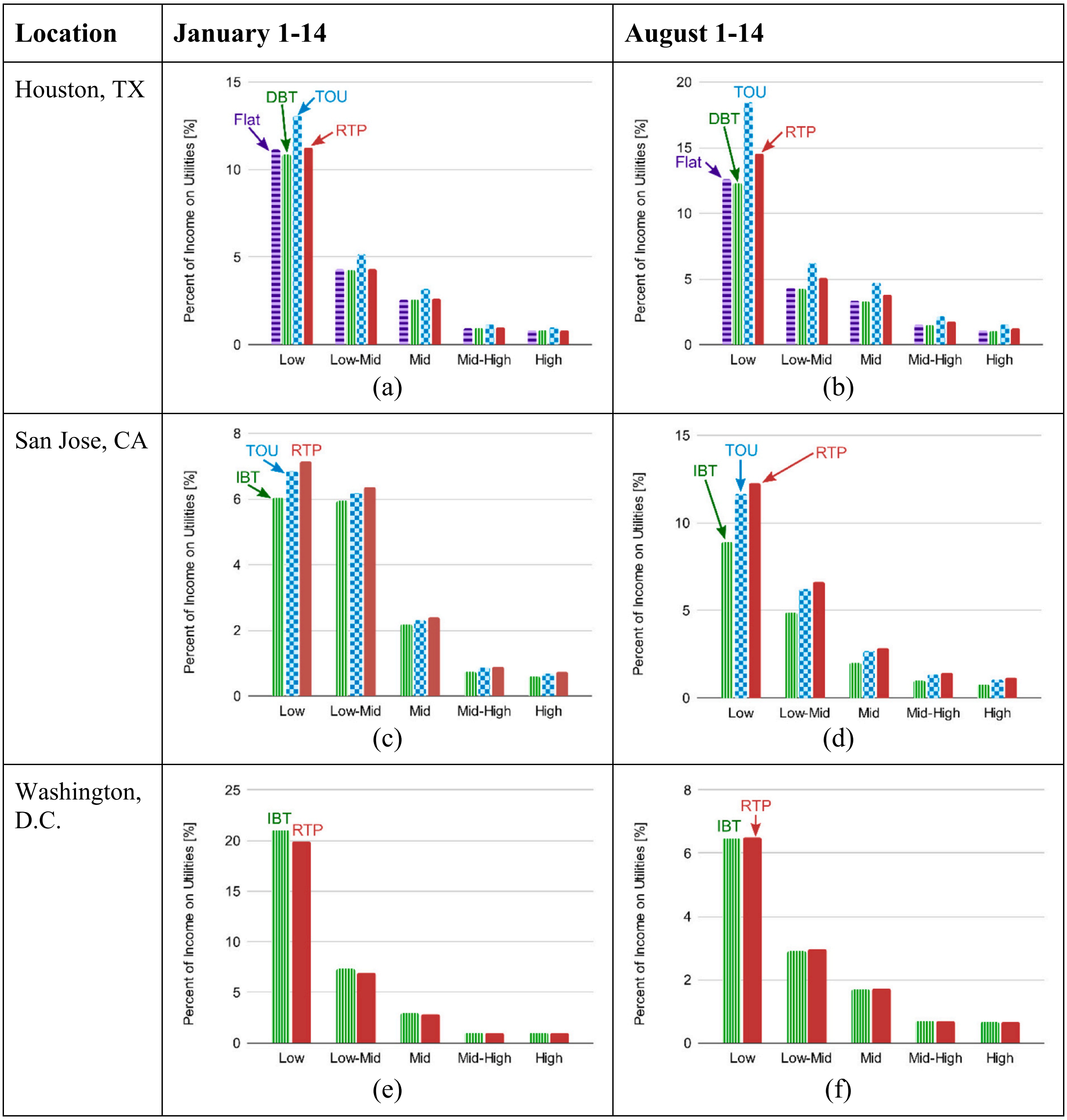

Fig. 6. The Percent of Income spent on Utilities (PIU) of various electricity pricing plans for each income level and location over a 2-week period. Note that the income level axis is not to scale in the figures for presentation purposes, but slope analysis was performed with metric value plotted against the corresponding income level's average income value. PIU is a measure of the financial burden on households caused by electricity bills under certain pricing plans. As such, a greater PIU indicates that households spend a higher proportion of their income on electricity bills. Bills are calculated using the energy consumption data of simulated households and PIU values were calculated using the average electricity bill for each income level. Only pricing plans offered by utility companies in each area and Real-Time Pricing (RTP) are modeled. The plans include: flat-rate, Decreasing Block Tariff (DBT), Time of Use (TOU), and Increasing Block Tariff (IBT). Flat-rate pricing maintains a constant price per kWh. DBT and IBT decrease and increase price per kWh with increasing consumption, respectively. RTP bases the price off the real-time wholesale market, and TOU increases price during historical periods of high demand.

income. For broader economic analysis, PIU can compare utility costs to the average income in a region. However, a limitation of PIU is that it can be difficult to compare the effects of new tariff plans, since the average income of each bracket tends to dominate the PIU values.

4.3. Change in percent of income spent on utilities from the baseline (ΔPIU)

ΔPIU compares the effects of new tariffs in terms of relative burden, which are shown in Fig. 7. Under five of the six scenarios considered, low-income households are affected the most by changing to time-variable pricing plans.

In Houston, TX, changing to DBT benefits low-income households the most according to ΔPIU. Cost increases by TOU and RTP are exacerbated in the summer when households are likely to rely on air conditioning during peak price times. TOU is especially detrimental to low-income homes, since they pay 1.9% and 5.9% more compared to fixed pricing in the winter and summer, respectively. RTP is relatively fair in the winter, with no income group changing >0.11%. However, in the summer, low-income households pay 2.0% more under RTP while high-income households only pay 0.2% more.

For San Jose, CA, both TOU and RTP cause increased burden as

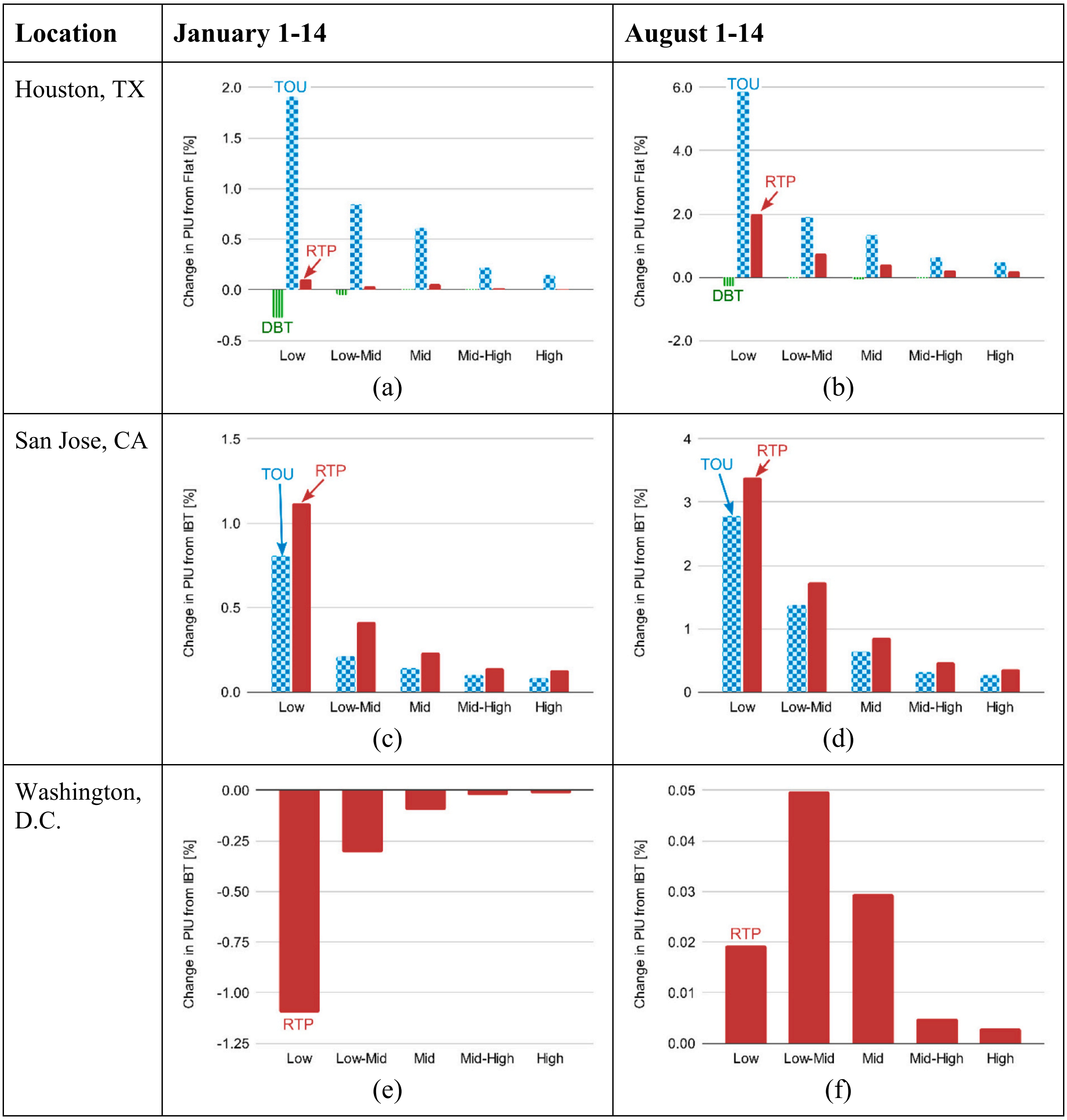

Fig. 7. Change in Percent of Income spent on Utilities (ΔPIU) of various pricing plans for each income level and location over a 2-week period. Note that the income level axis is not to scale in the figures for presentation purposes, but slope analysis was performed with metric value plotted against the corresponding income level's average income value. ΔPIU is a measure of how Percent of Income spend on Utilities (PIU) changes when transitioning from a baseline pricing plan to a new plan. As such, a positive ΔPIU indicates that households spend a higher proportion of their income on electricity bills after the transition to a new plan. Bills are calculated using the energy consumption data of simulated households. ΔPIU values were calculated using the average electricity bill for each income level. Different pricing systems are modeled are those offered in each location and Real-Time Pricing (RTP). The simplest pricing scheme offered by utility companies at each location is used as the baseline. Houston, TX uses flat-rate pricing as a baseline, where price per kWh remains constant. San Jose, CA and Washington, D.C. use Increasing Block Tariff (IBT), as a baseline, where price per kWh increases with increasing brackets of consumption. Each location is transitioned to other pricing plans offered, including Decreasing Block Tariff (DBT), and Time of Use (TOU). DBT decreases price per kWh with increasing consumption, RTP bases the price off the real-time wholesale market, and TOU increases price during historical periods of high demand.

income level decreases. RTP is generally about 25% to 33% more burdensome than TOU. The increase is larger during the summer, when ΔPIU increases up to 3.4% for low-income and 0.4% for high-income households.

In contrast, Washington, D.C. provides an example of pricing that becomes fairer using RTP over the existing IBT. In the winter, the lower a household's income, the larger the reduction in PIU. In addition, Washington, D.C. has a ΔPIU $<0.05\%$ for all income levels in the summer, which indicates that changing to RTP will not significantly impact households in any income level.

4.4. Comparative analysis

This section uses the proposed slope analysis method to compute and compare the level of fairness determined with the SCB, PIU, and ΔPIU metrics. To compare metrics, the average annual income of each income level was plotted against the corresponding SCB, PIU, or ΔPIU value. A linear trendline was fit to the data and the slope was used to determine

Table 2
Probability that a given pricing plan is fair using the Savings Compared to Baseline (SCB) and Change in Percent of Income spent on Utilities (ΔPIU) metrics for each location, time period, and new tariff. The baseline tariffs considered are Flat-rate for Houston, TX and Increasing Block Tariff (IBT) for San Jose, CA and Washington, D. C. Baseline tariff is different across locations due to the utility providers in those areas providing different plans. New pricing plans include Decreasing Block Tariff (DBT), Time of Use (TOU), and Real-Time Pricing (RTP). The probabilities are calculated by performing a *t*-test on the slope of a linear trendline fitting the plot of metric values against income level to determine if the slope of the line truly indicates fairness. For SCB, a negative slope indicates fairness; for ΔPIU, a positive slope indicates fairness. A probability of 1 would indicate that the pricing is fair, whereas a probability of 0 would indicate that the pricing is unfair. A deviation from zero or one indicates a level of uncertainty in the fairness conclusion.

Location	Period	Baseline Tariff*	New Tariff	Probability of fairness, SCB [%]	Probability of fairness, ΔPIU [%]
Houston, TX	January 1–14	Flat Rate	DBT	89.5	89.4
			TOU	55.6	3.0
			RTP	81.1	3.2
	August 1–14		DBT	50.2	88.3
			TOU	32.1	6.3
			RTP	50.7	5.8
San Jose, CA	January 1–14	IBT	TOU	80.5	8.4
			RTP	84.2	5.5
	August 1–14		TOU	94.6	3.0
			RTP	98.8	2.8
Washington, D.C.	January 1–14	IBT	RTP	99.4	92.8
	August 1–14		RTP	29.2	7.3

the probability of a transition between pricing plans being fair, as described in Section 2.4. Note that in Figs. 5-7, the income level axis is not to scale to enhance readability, but for slope analysis the income level axis was scaled to match the metric value with the average income for the corresponding income level. Recall that, when fair, the SCB trendline has a negative slope, PIU has a positive slope, and ΔPIU has a positive slope. As the level of fairness approaches 100%, a plan is considered fair, and if the probability is near 0%, a plan is considered unfair. If the probability of fairness is near 50%, the conclusion has high uncertainty and is inconclusive. The level of fairness determined by the metrics for each pricing plan considered are shown in Tables 2 and 3.

The following paragraphs will discuss the results shown in Tables 2 and 3. Note that PIU categorizes all of the plans considered as unfair, so it will not be discussed in as much depth. This is because PIU is an absolute measure of fairness defined by equitable electricity cost burden and the total cost of electricity between the highest and lowest income brackets changes much less than the total income earned.

Table 3
Probability that a given pricing plan is fair using the Percent of Income spent on Utilities (PIU) metric for each location, time period, and tariff. Tariffs considered are Flat-rate, Increasing Block Tariff (IBT), Decreasing Block Tariff (DBT), Time of Use (TOU), and Real-Time Pricing (RTP). Tariffs vary by location due to the utility providers in each area providing different plans. The probabilities are calculated by performing a t-test on the slope of a linear trendline fitting the plot of metric values against income level to determine if the slope of the line truly indicates fairness. For PIU, a positive slope indicates fairness. A probability of 1 would indicate that the pricing is fair, whereas a probability of 0 would indicate that the pricing is unfair. A deviation from zero or one indicates a level of uncertainty in the fairness conclusion.

Location	Period	Tariff type	Probability of Fairness, PIU [%]
Houston, TX	January 1–14	Flat	4.9
		DBT	4.7
		TOU	4.6
		RTP	4.8
	August 1–14	Flat	5.5
		DBT	5.4
		TOU	5.8
		RTP	5.6
San Jose, CA	January 1–14	IBT	0.7
		TOU	0.7
		RTP	0.7
	August 1–14	IBT	2.4
		TOU	2.5
		RTP	2.5
Washington, DC	January 1–14	IBT	6.1
		RTP	6.0
	August 1–14	IBT	3.8
		RTP	3.7

In Houston, TX, DBT pricing has a high level of fairness in the winter under both metrics, but SCB is inconclusive in the summer while ΔPIU is still able to make a conclusion about fairness. SCB is also unable to reach a clear judgment on TOU in both seasons and RTP in the summer, showing one of its limitations. When there is less of an obvious trend in the absolute increase or decrease, SCB has a large standard deviation and a slope close to 0, causing the result to be inconclusive. However, ΔPIU can render a judgment in cases where all income levels experience a bill increase or decrease of similar magnitude, because the effect on the lower-income levels will be greater due to their relatively smaller annual income.

The San Jose, CA results provide situations where SCB and ΔPIU reach opposing conclusions on the level of fairness. SCB claims that all new pricing plans tend to be fair, with high certainty for the summer and lower certainty in the winter. According to ΔPIU, all new plans are unfair. In the winter, ΔPIU concludes that the price is unfair with 8.4% and 5.5% uncertainty, whereas SCB has 19.5% and 15.8% uncertainty in concluding pricing is fair. The higher penalty incurred by the low-income households reduces certainty under SCB despite the clear increasing trend from low-mid-income to high-income households. Additionally, based on intuition and the utilized fairness definition, the higher cost increase to low-income households in the winter is unfair, but SCB concludes these plans are fair, highlighting another weakness. SCB cannot accurately determine fairness when one income level is disproportionately impacted. Conversely, under ΔPIU, there is a clear trend as income level increases for all of the San Jose cases.

Both ΔPIU and SCB reached the same conclusion for RTP in Washington, D.C. for both seasons. RTP in the winter benefits lower income levels the most with a consistent trend, and both metrics capture that it is fair. Although RTP in the summer is labeled as unfair using slope probability analysis and all incomes have negative SCB, the ΔPIU values change no >0.05% for any income level. Since the magnitude of the effect on customers' burden is relatively small, if the goal is to minimize ΔPIU for all income levels, the RTP tariff may still be fair enough. Of the locations examined, Washington, D.C. is the only one to have improved fairness over the baseline plan if RTP is implemented.

The high uncertainty of fairness and misleading conclusions that occurred under SCB render it unsuitable as a single metric to judge if transitioning to certain pricing systems exhibits fairness. SCB had >20% uncertainty in 33.3% of the situations and stated that a plan was fair despite disproportionate impact on one income group in 41.6% of cases. In contrast, ΔPIU could determine fairness with no >12% uncertainty for every case simulated. ΔPIU labeled all cases when one income level was disproportionately penalized as unfair. The magnitude of the ΔPIU values should be considered along with the probability of fairness to account for situations when the effect is negligible on all groups. Intuitively, it is more likely for ΔPIU to show a clear trend because annual income typically changes by a greater percentage compared to the utility bills between income levels. While PIU did not demonstrate a useful result with the tariffs demonstrated in this work, it may be useful in situations when the fairness goal is for all households to experience equal electricity cost burden.

Overall, these results indicate that DBT can be fair in the Houston, TX region. Time-variable pricing is unfair particularly to low-income customers in Houston, TX and San Jose, CA. However, RTP shows promise for implementation in Washington, D.C., with a high probability of fairness in the winter and ΔPIU values for all income levels $<0.05\%$ in the summer. The financial impact on each income level depends on location, specific formulas for each tariff, and season. The absence of a single recurring pattern at every location is consistent with the lack of consensus in literature [3,12–15,18,19]. The fact that utility companies implement pricing plans such as TOU and RTP differently also contributes to the variation. The inconsistencies discovered when comparing studies across differing locations indicate the importance of testing models made specifically for each location before implementing electricity price changes.

5. Conclusion

This paper proposed a broadly applicable method for quantitatively determining the level of fairness exhibited by electricity pricing plans. Fairness is defined in terms of consumer and group fairness, such that an equitable relative or absolute financial burden across income levels is desirable. The method calculates the level of fairness exhibited by a pricing plan by performing a null hypothesis test on the slope of a linear trendline fitting annual income against the fairness metric values. The performance of three fairness metrics was evaluated using simulated household energy consumption from a novel combination of income-specific household model generation and co-simulation for advanced HVAC control. Simulated household consumption was validated against the consumption of surveyed households with correlation analysis. Ten houses were modeled for each income level to account for diversity between houses. Electricity consumption by simulated households across 3 US climate zones was used to compute electricity bills under various tariffs, and the fairness metrics were applied to the average bill for each income level to evaluate their performance. The SCB and ΔPIU metrics provide the probability that a pricing scheme is fair relative to an existing tariff, whereas PIU measures the fairness of a single tariff.

The merits of the SCB, PIU and ΔPIU metrics were demonstrated through several cases. SCB computes changes in utility revenue from the residential sector, but results demonstrate the limitations of difference-based metrics. The SCB slope test may yield misleading results if all households have a similar rate increase, when lower-income customers suffer disproportionate impact due to their smaller overall budget. Further, SCB can falsely conclude a tariff is fair if one income level is penalized disproportionately but the other four income levels show a consistent slope. PIU emphasizes disparities in the ability for households to pay the utility bill. PIU could be useful if the goal is to make households in each income bracket pay the same average percentage of their income, or to ensure no household pays more than a certain percentage of their income. However, difference in income has a greater effect than changing the pricing system in the cases studied, making PIU less useful for comparative analysis between tariffs. For the purpose of quantifying changes in equity of a new electricity pricing system relative to existing tariffs, ΔPIU provides a single metric for the difference in burden on households by income level. The probability of having a positive slope for ΔPIU provides a quantitative measurement of the fairness level of a new tariff and can be used in conjunction with the absolute value of ΔPIU values to conclude whether a tariff is fair.

Future research can apply the framework for generating realistic and diverse household energy models from public survey data to study a wide variety of locations and demographic traits. Household models can be used in conjunction with the slope analysis method and chosen fairness metric to evaluate the effects of novel electricity tariff systems to different groups within the population. Future researchers may desire to make household models demand elastic, especially as technological and policy developments make demand response more accessible and common-place. Demand elasticity may also become significant when studying certain marginal cases of purchasing energy, such as during natural disasters or power shortages. The model generation method may also need to be expanded to include types of housing other than single-family homes or further disaggregate simplifications made in this work to more broadly study energy fairness. Furthermore, while the ΔPIU metric shows potential for fairness evaluation, fairness metrics may need to be further developed for each location's particular needs and culture. The strengths and limitations of the metrics considered in this study, particularly ΔPIU, can serve as a framework for future formulation of viable fairness metrics. Finally, fairness analysis can be extended to consider the impact of pricing plans on utility companies, other customer types, and grid stability. For broader analysis, provider fairness, as described by Ekstrand et al. [7], can also be considered. This framework enables researchers and policymakers to quantify and iteratively improve the fairness of new electricity tariff systems prior to implementation.

CRediT authorship contribution statement

Hannah Covington: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation. **Brian Woo-Shem:** Writing – review & editing, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Chenli Wang:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Thomas Roth:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Cuong Nguyen:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Yuhong Liu:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Yi Fang:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Hohyun Lee:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of Competing Interest

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Data availability

Data will be made available on request.

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