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Research Paper

Novel Electricity Pricing Method Based on the Customers' Risk Aversion Function

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Abstract— *Electricity pricing approaches are generally categorized into flat-rate and dynamic pricing models. Flat-rate pricing charges a fixed rate regardless of market conditions, whereas dynamic pricing adjusts rates based on system and market factors. Traditional pricing methods often lack flexibility, preventing consumers from choosing their preferred pricing plans. This study introduces a Selective Electricity Pricing (SEP) model that allows customers to select a Maximum Tolerable Price (MTP) tailored to their needs and benefit from Real-Time Pricing. The SEP model also includes a retailer-funded mechanism to shield customers from high market prices, acting as a risk hedge. Using a risk aversion function to gauge consumer preferences, the SEP method was implemented on the IEEE-24 test system. Results indicate that low-risk customers are more likely to engage in dynamic pricing. The SEP model significantly outperforms flat-rate pricing, yielding 17.27% higher retailer profits, 11.32% lower demand, and a 2.73% increase in average customer payments, compared to a 2,500MW drop under flat-rate pricing.*

Keywords—Retailer, electricity pricing, risk aversion function, electricity market.

NOMENCLATURE

Abbreviations

CARA	Constant absolute risk aversion
CPP	Critical peak pricing
FPT	Fixed-price tariffs
MTP	Maximum tolerable price
PVP	Peak-valley pricing
RTP	Real-time pricing
SEP	Selective electricity pricing
TOU	Time-of-use

Functions

$\mu(.)$	Weighted average price function
$\xi(.)$	Market benefit function
$E(.)$	Expectation function
$R(.)$	Risk aversion function
$S(.)$	Customer benefit function
$U(.)$	Utility function
$Var(.)$	Variance function

Indices and Sets

i, j, k	Time indices
N	Number of customer
n	Customer index
T	Size of time period

Variables and Parameters

π_p^+	Selective electricity pricing contract premium
π	Electricity price
π_0	Initial electricity price
π_P	Maximum tolerable premium
π_{cus}	Customer's payment for electricity energy
π_{fix}	Fixed part of customer's payment
π_{MTP}	Customer's maximum tolerable price
π_{var}	Variable part of customer's payment
$\pi_{\pi_{MTP}}$	Electricity market price after selecting π_{MTP} for all of the customers
D_0	Initial electricity demand
$D_{\pi_{MTP}}$	System demand after selecting π_{MTP} for all of the customers
D	Electricity demand
k	Premium loading coefficient
r	Risk aversion coefficient
Re	Reimbursement
w	Customer's wealth
x	Cost of risk

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1. INTRODUCTION

Initially, consumers struggled to engage in the electricity market due to limited knowledge and inadequate infrastructure during the early stages of power system restructuring. Today, many consumers avoid participating in the electricity market because of significant price volatility, despite the established structure. In the electricity market, production units compete by offering their prices to the independent system operator (ISO), which sets electricity prices for different hours through a market clearing procedure. The market price fluctuates significantly due to variations in electricity consumption [1]. Fig. 1 illustrates the daily real-time market price fluctuations for the PJM market [2]. To achieve a fully liberalized power system, a framework must be established allowing consumers to freely choose their services and participate in the market. Thus, a mechanism should be developed to motivate consumer participation and address concerns related to market involvement, offering tailored service options for individuals [3].

Market prices should signal consumers to adjust their demand based on system conditions, such as shifting consumption to off-peak hours when prices are high during peak times. Price signals in the wholesale electricity market help clarify transmission network and generation unit conditions [4]. Real-time pricing (RTP) is a highly effective method for electricity pricing, exposing customers to wholesale market prices and encouraging them to adjust consumption based on market signals. This approach can reduce consumption during peak periods or shift it to off-peak times, thereby decreasing price fluctuations and average market prices. Despite the benefits of RTP, several barriers restrict consumer participation, including the following [5].

- Inappropriate market structure and lack of incentives.
- Inexperience and intricacy of participating in the market.
- Costs of measurement and communication infrastructure.
- Economic risks and market price volatilities.

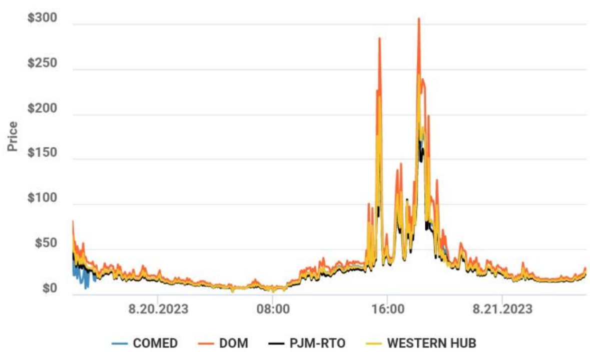

Fig. 1. RTP in PJM [2].

End users prefer to purchase their electricity energy through fixed-price tariffs (FPT) due to the above-mentioned barriers, leading to their protection against the risk of electricity market price volatility. A well-designed risk hedging mechanism protects the customers against the market risk in addition to the FPT [6]. Risk hedging contract enables the customers to manage electricity cost properly by sharing the market risk with the risk hedger. From a risk hedging perspective, the customers' payment for their energy usage contains two components including the risk hedging premium and variable cost of supply. The consumer pays the average market price as the premium in FPT, which fully covers market price fluctuations. In addition, the customer assumes full self-risk and pays the variable market price in RTP [7].

Common approaches used in behavioral economics and decision-making experiments to elicit individuals' risk preferences and measure their attitudes towards risk. These approaches include the Multiple Price List (MPL), Certainty Equivalent (CE), Lottery Choice, and Portfolio Choice. MPL presents participants with choices between certain and uncertain outcomes to infer risk preferences. CE equates risky options with certain amounts, directly measuring utility functions. Lottery Choice involves selecting between different probabilistic options, while Portfolio Choice analyzes investment decisions under uncertainty. Each method offers unique advantages and limitations, and the suitability of a particular method depends on the research context and objectives.

Different electricity energy pricing methods were assessed before. For example, [12] discussed dynamic electricity pricing as one method of demand side management. They reported that the electricity customer preferences have been neglected so far, despite their significance in determining the most widely used electricity pricing regime selected by consumers and its reason. The results represented that consumers prefer a simple pricing regime to complex and highly dynamic programs, despite their interest in dynamic pricing. Thus, the customers gradually prefer dynamic pricing regimes while faced with the opportunity to select among different ones. Appropriate advertising campaigns should inform the customers regarding the benefits of dynamic pricing due to the lack of transparency for individual and social advantages. Taherian *et al.* [13], present a novel model for short-term electricity price forecasting that leverages similar historical days and price data. The key contribution of their work is the development of an intelligent forecasting model based on a multilayer perceptron neural network, with a focus on structural and weight optimization to enhance model performance. The results of applying this forecasting methodology to the Market Clearing Price (MCP) data from the Iranian and Nord Pool electricity markets show its effectiveness and robustness in providing reliable short-term price predictions.

Electricity pricing can be employed as a political mechanism to obtain political objectives and win elections. Electricity pricing brings different individual and social effects. For instance, [14] evaluated electricity pricing with political objectives in India. Some parties manipulate electricity pricing to attract the majority of the society, which may result in ignoring the rest of the society. In addition, dynamic pricing can be designed to increase renewable generation impact in power system. Further, [15] designed dynamic pricing for household electricity customer to minimize his/her electricity bill. The customer can optimally decide about the method of buying electricity from the grid or using his/her local resources, batteries, and PV utilizing the aforementioned pricing method. Furthermore, [16] compared different electricity pricing methods, time-of-use (TOU), RTP, critical peak pricing (CPP), and emergency demand response. Based on the results, the intensity and range of price fluctuations in RTP are more than that in TOU. For example, price changes intervals for RTP and TOU in European markets last one and four hours, respectively. A notification signal is sent to customers through the CPP and emergency demand response systems to reduce their consumption during peak hours and in the event of an emergency, respectively. In another study, [17] argued that different pricing regimes can be combined. For instance, TOU can be combined to a separate charge to decrease more demand during the peak time intervals. They surveyed electricity retail cost which contains two parts including electricity wholesale price, as well as regulated and administrated one. Peak-valley pricing (PVP) is considered as another dynamic electricity pricing. [18] examined the method of applying PVP in different provinces of China. In order to achieve the objectives of restructuring in the power system, the pricing should be customized for different customers in addition to dynamic pricing. In addition, [19] proposed a clustering method to classify electricity customers to provide electricity retail price based on the customers' load profile. Providing pricing based on the customers' individual perspectives was ignored although different electricity pricing methods were investigated before. The value of electricity, which varies for different loads, depends highly on its benefits to each consumer. However, conventional retail electricity pricing mechanisms are usually based on the cost of electricity supply rather than the value of electricity to the consumer. Further, [20] developed a dynamic electricity pricing model which considers the consumption value from the consumers' perspective. Furthermore, [21] studied dynamic electricity pricing mechanisms and claimed that the current price volatility does not generate enough savings to compensate for the additional costs of smart meters in a household. They proposed employing 'Ad-valorem' taxation based on the prices of energy exchange to increase the motivation for load shifting. High prices increases the imposed taxes. Such taxation mechanism strengthens the price signal, creates incentives for load shifting, and justifies investments in smart grids.

In [22], the authors present a risk-aware approach that enables the EV aggregator to make more informed decisions when participating in both the forward and spot electricity markets to procure energy for their EV customers, as well as set optimal

Table 1. Methods for assessing risk preferences in behavioral economics experiments.

Method	Advantages	Disadvantages	Potential application in electricity pricing
Multiple Price List (MPL) [8]	Simple, incentivized, can be combined with other experiments	Sensitive to probability weighting, requires expected utility framework	Can be used to elicit risk preferences of electricity consumers to inform pricing strategies
Certainty Equivalent (CE) [9]	Directly measures utility function, flexible	Subjective, prone to anchoring effects, requires strong understanding of economic concepts	Can be used to determine the monetary value consumers assign to uncertain electricity prices
Lottery Choice [10]	Simple, intuitive	Can be influenced by framing effects, limited in capturing risk attitudes	Can be used to assess consumer preferences for different electricity pricing options with varying levels of uncertainty
Portfolio Choice [11]	Real-world relevance, captures complex risk preferences	Requires complex calculations, data availability might be limited	Can be used to analyze consumer investment decisions in electricity-related assets under uncertainty

charging and discharging prices that balance profitability and serve the interests of their EV customer base. The inclusion of the risk aversion component is a critical aspect of this work, as it allows the EV aggregator to navigate the inherent uncertainties in electricity prices and EV behavior more effectively, enhancing their ability to thrive in the dynamic and uncertain electricity market environment.

Different electricity pricing methods were considered via the risk aversion concept. For instance, [23] reviewed the impact of the risk aversion concept in zonal and nodal electricity markets considering generation units' vision. In another study [24] assessed the risk aversion behavior in power plant investors. The results indicated that investors with a neutral risk aversion function tend to invest in base load in addition to increasing production capacity at peak. Furthermore, [25] evaluated the impact of risk aversion from different market perspective. The results represented that the effect of risk aversion is more influenced by a market with nodal pricing compared to that with imperfect locational price signals. In fact, transmission companies which neglect risk aversion of generation ones imposes additional costs to the system. In addition, [26] selected the risk aversion concept to study electricity retailer's risk due to purchasing energy from the wholesale electricity market. To this aim, the risk aversion concept was used to identify electricity pricing effects on the end-use electricity customers and their decision behavior against different electricity purchasing contracts. Further, [27] designed an optimal price tariff for a risk-averse electric retailer which participates in the pool electricity market. The results revealed that the degree of risk aversion of the retailer strongly influences contracting decisions significantly, while the price sensitivity of consumers imposes a greater impact on the selling price offered. In another study, [28] developed a new retail electricity pricing method to mitigate the impact of risk arising from the unpredictable generation of renewable energy sources. To this aim, a conditional value-at-risk (CVaR) optimization framework was utilized to ascertain the retail electricity prices for the following day. The results indicated that applying risk-averse conditions reduces the standard deviation (SD) in optimal retail prices and expected cost unlike non-risk conditions. Some studies considered the behavior aspect of the electricity pricing. For example, [29] provided insights from psychology and behavioral economics to determine the method of designing, presenting, and implementing dynamic pricing to improve customers' willingness to participate in the electricity market. Goyal *et al.* [30] presents a comprehensive approach to dynamic pricing that benefits both consumers and utility providers. Notably, the implementation of dynamic pricing on consumers resulted in reduced electricity bills, demonstrating the bi-directional advantages of this strategy. The holistic approach outlined in this work provides a valuable framework for utility providers to optimize their operations and pricing structures, while simultaneously delivering cost savings and improved sustainability to their customer base.

A notable trend in these studies is the recognition of risk aversion as a crucial factor influencing decision-making processes within the electricity sector. However, the level of sophistication in modeling risk aversion and its integration into practical applications differs across the examined papers. While some studies propose innovative approaches, others provide valuable insights into specific aspects of the problem, such as bidding strategies or microgrid management.

The provided table offers a comparative overview of various studies investigating the interplay between risk aversion and the electricity market. The research papers encompass a broad spectrum of topics, ranging from modeling consumer behavior and welfare to strategic decision-making in the electricity industry. While some studies delve deeply into the quantification of risk aversion and its impact on electricity demand, others explore its implications for pricing, market participation, and grid management. Although the focus varies, the overarching theme is the significance of risk aversion in shaping the electricity landscape.

The present study aims to propose a new selective electricity pricing (SEP) method by which the customers can select their preferable maximum tolerable price (MTP) among various options due to the advantages of RTP and proper risk hedging mechanism to cover customer risks. The customer buys energy with the market price when this price is lower than the selected MTP. Further, the retailer should pay the difference of market price and predetermined MTP when this price is higher than the selected MTP. Retailer receives premium in turn of reimburse consumers. Thus, all of the customers can participate in the electricity market and the retailers guarantee their risks coverage adequately. The selected MTP depends highly on the customer's type and needs. Here, risk aversion concept is utilized to determine the customers' needs and preferences due to the design of efficient SEP contracts. This study proposes a pricing method in which the retailer provides a table of contracts. Each customer selects a contract from the table based on his/her perspective. The concept of risk aversion from the microeconomics is employed to measure the customers' perspective.

The main contributions of the present study can be summarized as follows.

1) The SEP model allows customers to select their preferred maximum tolerable price (MTP) from various options. This provides customers with the flexibility to choose a pricing plan that best suits their individual needs and risk preferences.
2) The study incorporates the benefits of RTP by allowing customers to purchase energy at the market price when it is lower than their selected MTP. This enables customers to take advantage of favorable market conditions and potentially reduce their electricity costs.
3) The SEP method includes a mechanism where the retailer

Table 2. Risk aversion in electricity markets.

Paper title	Advantage	Disadvantage	Method	Result
[31]	Proposes a novel model to estimate electricity customers' behavior using risk aversion coefficients.	The customers' welfare is modeled only as a function of electricity price and risk aversion coefficients.	Formulates an economic load model and utilizes it to estimate price elasticity and income elasticity of electricity demand.	As the risk aversion coefficient increases, consumers achieve more satisfaction from electricity consumption.
[32]	Introduces a standard methodology for uncertainty modeling techniques in decision-making processes.	Not specifically focused on electricity pricing.	Uses an expected utility function to model risk aversion.	Provides insights into decision-making under uncertainty.
[33]	Addresses both electricity price modeling and risk management.	May not delve deeply into risk aversion.	Investigates electricity price processes and portfolio risk management.	Offers a comprehensive view of electricity markets.
[34]	Proposes a risk-based bidding strategy for a generation company participating in an electricity multimarket.	Focuses on joint energy and reserve markets rather than risk aversion.	Addresses the interaction between energy and reserve markets.	Provides insights into bidding strategies.
[35]	Introduces a stochastic risk-averse model for pricing energy.	Limited details available.	Incorporates risk aversion in energy pricing.	Useful for understanding risk-aware pricing.
[36]	Explores energy management in networked microgrids.	Not exclusively focused on pricing.	Considers risk aversion in microgrid management.	Relevant for understanding risk-aware decision-making.

pays the difference between the market price and the customer's predetermined MTP when the market price is higher. This serves as a risk hedging mechanism, protecting customers from price volatility and uncertainties in the electricity market.

4) The proposed approach encourages broader customer participation in the electricity market, as the SEP model provides a framework for all customers to engage and manage their electricity consumption and costs.
5) The study recognizes the importance of considering the customer's type and needs in determining the appropriate MTP. By utilizing the risk aversion concept, the SEP method can be tailored to meet the specific preferences and requirements of different customer segments.

The remainder of this study is organized as follows. Section 3 describes the proposed SEP. Section 4 focuses on the results. Finally in Section 5, conclusions are presented.

2. Risk aversion modeling

People behave differently while faced with risky situations. Risk aversion theory classifies people in three groups including risk-averse, risk-neutral, and risk-seeking based on their behavior. Expressing the customers' behavior requires a function to mathematically interpret such behaviors. To this aim, utility function is proposed in the microeconomics which quantifies risk aversion behaviors of different customers. This function provides a useful model for assessing the method of decision making by people. A risk-averse person with a concave utility function avoids accepting risk. Such person tends to pay cost more than the value of the damage to avoid the risk. The person does not response to risk (risk-neutral) when the utility function is linear. Some people tend to pay less than risk value to avoid risk. Such others have a convex utility function and are called risk-seeking who tend to gamble. Fig. 2 illustrates utility function for different people.

From a microeconomic perspective, the behavior of different customers can be modeled by their utility functions to identify their needs and provide appropriate services [37]. Some studies consider the concept of a utility function while evaluating the behavior of energy customers. In addition, [38] examined the utility function of customers to determine incentive payments for participants in time-based demand response programs. Further,

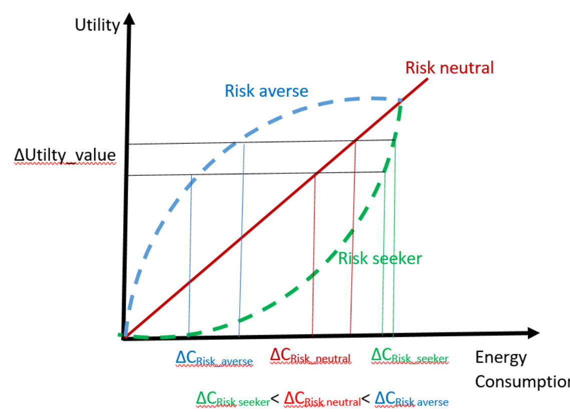

Fig. 2. Utility function for different risk aversion behavior.

[39] investigated the dynamics of electricity markets using an unknown utility function from the customer's viewpoint and a cost function from the utility company to determine the market price. Furthermore, [40] designed an insurance mechanism to update the distribution network by considering the impact of the customers and distribution company utility functions.

While a zero-price for electricity may seem ideal from the customer's perspective, it is not a practical or sustainable solution in a real-world electricity market. Basing the pricing on the customer's risk aversion function can help find a balance between customer preferences, cost recovery, and system reliability, which is a more rational approach. Based on the principle of expected utility function, a rational customer selects an investment which maximizes his/her expected utility function. Therefore, this function can be utilized to measure customers' preferences for different investment levels [41]. Here, utility function is represented by $U(w)$, where w is regarded as the customer's wealth due to electricity energy consumption. More formally, utility function represents the level of satisfaction for each customer obtained by electricity power consumption. The utility function is considered as a twice-differentiable one with properties of non-satiation and risk aversion (Eqs. (1) and (2)) hypothesizing that electricity customers are risk-averse against consumption. The non-satiation property indicates that an increase in the consumption raises the utility, meaning that more consumption is preferred to less one [42].

Based on the risk aversion property, utility function is regarded as concave. In other words, an increase in the consumption decreases the marginal utility of wealth. The principle of utility function emphasizes that electricity consumption has higher value than its cost, and customers tend to pay higher risk hedging cost than the exact value of consumption.

$$\frac{\partial U(w)}{\partial w} \geqslant 0 \tag{1}$$

$$\frac{\partial U^2(w)}{\partial w^2} \leqslant 0 \tag{2}$$

where U is the utility function, which represents the customer's overall satisfaction or well-being, and w is the customer's wealth. Risk hedging premium can be calculated by applying the expected utility function. For electricity sector, the customer selects risk hedging contract with premium π_P to be protected against the risk when the utility function of the $w - \pi_P$ is equal to or greater than the expected utility (E) of the $w - x$, where x represents the cost of risk based on Eq. (3).

$$E[U(w-x)] \leqslant U(w-\pi_p) \tag{3}$$

Eq. (4) is achieved by expanding both sides of Eq. (3) through Taylor series in the neighborhood of $w - E[x]$ [21].

$$\begin{aligned} U(w-\pi_p) &\cong U(w-E[x]) + \\ &[E[x]-\pi_p]U'(w-E[x]) \end{aligned} \tag{4}$$

$$\begin{aligned} U(w-x) &\cong U(w-E[x]) + [E[x]-x]U'(w-E[x]) + \\ &\frac{[E[x]-x]^2}{2}U''(w-E[x]) \end{aligned} \tag{5}$$

Thus, the maximum tolerable premium can be obtained as follows.

$$\pi_p = E[x] + \frac{\text{var}[x]}{2}R(x) \tag{6}$$

where $R(x)$ indicates the risk aversion function, which can be calculated as follows.

$$V_{Co3} = \beta V_{\Delta-pri} \tag{7}$$

The utility function is needed to achieve a commutable expression for the maximum tolerable premium. A large variety of such functions may be considered [43]. In [44], π_P was determined with the constant absolute risk aversion (CARA) utility function which has an exponential shape based on Eq. (8), where r is regarded as the risk aversion coefficient. Therefore, the risk aversion function is determined as a constant coefficient and can be calculated as Eq. (9). Finally, the maximum tolerable premium is determined by Eq. (8).

$$U(x) = 1 - e^{-rx} \tag{8}$$

$$R(x) = r \tag{9}$$

$$\pi_p \cong E[x] + r\frac{\text{var}[x]}{2} \tag{10}$$

In CARA condition, the maximum tolerable premium is related to the average and variation of the risk cost and customer risk aversion coefficient.

3. SEP

Electricity energy is sold via the FPT by a fixed rate during the entire time period regardless of the electricity market fluctuations. However, electricity energy is sold in the dynamic-pricing by time varying rate which reflects the volatility of the wholesale market prices. Fig. 3 compares the fixed and RTP. The customer seeks to adjust his/her consumption with the market price signal when the electricity energy is sold by dynamic-pricing due to the close relationship between electricity demand and market price. However, this method exposes the customer to the risk of buying high price. This study proposes that the retailer provides different hedging contracts to protect customers against the market price risk. Such contracts are designed to relieve the customers concerns and facilitate their participation in RTP. Customers can make appropriate decisions based on their expected utility functions and select proper risk protection to hedge their intended amount of market price risk. In the proposed framework, each customer selects a maximum tolerable price (MTP) which is considered as the maximum price to purchase energy from the market. The customer purchases electrical energy when the market price is lower than the predetermined MTP. Otherwise, the retailer (risk hedger-company) pays the difference between the MTP and electricity market price (Fig. 4). In fact, the customer can decide about the amount of the price fluctuations risk transferred to the retailer and that taken when he/she can select different MTPs. In other words, the selected MTP is regarded as the deduction employed in insurances contracts. In turn, the retailer receives premium to compensate the difference between the market price and selected MTP.

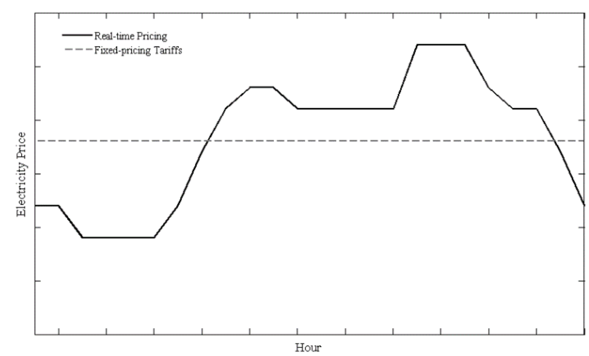

Fig. 3. Fixed-pricing tariffs versus RTP.

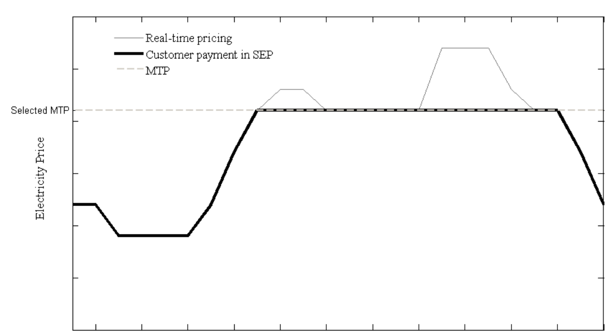

Fig. 4. Proposed SEP.

It is hypothesized that the customer's payment (π_{cus}) contains two parts (Eq. (11)) regardless of the electricity pricing regime. The first part is considered as the variable part, which covers the varying costs of supplying electricity energy (π_{var}), while the second part is regarded as the fixed part, which represents the risk hedging premium (π_{fix}). The power market price is covered entirely through the risk hedging contract when the retailer sells energy by FPT. Based on Eq. (12), the customer pays the expected value of the market price (π) as the premium. In addition, the customer payment is dictated by Eq. (13) when the SEP is selected. Here, the first part is considered as the premium rate, while the second part is regarded as variable, which depends on the market price and selected MTP (π_{MTP}). Finally, the customer does not select any risk hedging protection when he/she opts RTP. In other words, the customer selects full self-risk hedging. Thus, the premium equals zero and the variable price equals the market price (Eq. (14)).

$$\pi_{cus} = \pi_{\text{var}} + \pi_{fix} \tag{11}$$

$$\begin{cases} \pi_{fix} = E\left(\pi\right) \\ \pi_{\text{var}} = 0 \end{cases} \tag{12}$$

$$\begin{cases} \pi_{fix} = f\left(\pi_{MTP}\right) \\ \pi_{\text{var}} = \begin{cases} \pi & if \;\; \pi < \pi_{MTP} \\ \pi_{MTP} & if \;\; \pi \geqslant \pi_{MTP} \end{cases} \end{cases} \tag{13}$$

$$\begin{cases} \pi_{fix} = 0 \\ \pi_{\text{var}} = \pi \end{cases} \tag{14}$$

Table 3 compares the conventional pricing methods including FPT, RTP, and proposed SEP. As indicated, the customers are shielded from the market price volatilities in the FPT method. In return, the average market price remains high, which forces the customers to purchase electricity energy with the relatively high fixed rate. However, the customers face directly with the wholesale market price volatility risk in the RTP. In return, they can respond such volatilities and modify their consumption, which decreases mean value of the wholesale electricity price. In the proposed pricing method, each customer can select his/her purchasing method among different options to participate in the electricity market based on his/her viewpoint.

Selected MTP can be interpreted as load shifting ability of the customer. The customer requests low level of risk hedging by increasing the ability to shift his/her demand because he/she can respond to the market price based on the concept of price elasticity of the demand. However, the customer who fails to manage his/her consumption requests higher risk hedging level. The concept of price elasticity is used to interpret the customers' ability to the consumption modification based on the electricity pricing variation [45]. The price elasticity of the i^{th} period versus the j^{th} period can be dened as follows.

$$\varepsilon(i,j) = \frac{\partial D(i)/D_0(i)}{\partial \pi(j)/\pi_0(j)} \tag{15}$$

where D, π, and ε represent the electricity demand, market price, and elasticity, respectively. Self- and cross-elasticity are considered as two types of elasticity. Self-elasticity (cross-elasticity) refers to the percentage of demand change in response to a 1% change in its price (another time price). Demand changing due to different SEP contracts is described here based on the risk aversion concept.

3.1. Effect of SEP on demand in single period

An economic load model is developed here to consider the changes of the customer's demand with respect to altering the MTP. It is hypothesized that the customer's demand changes from $D_0(i)$ (initial value) to $D(i)$ in response of the market price variations due to the SEP implementation [46]. Therefore, the demand changing is defined as follows.

$$\Delta D(i) = D(i) - D_0(i) \tag{16}$$

The customer's benet (S) is defined as Eq. (17) after the SEP implementation when $U(D(i))$ represents his/her utility function for $D(i)$ kWh consumption.

$$\begin{aligned} &S = U(D(i)) - [\pi(i) + \pi_p]D(i) + \\ &[\pi(i) - \pi_{MTP}]D(i) \end{aligned} \tag{17}$$

where $\pi(i)$ is considered as the market price of i^{th} time period. Maximizing the customer's benet requires the following equation.

$$\frac{\partial S(i)}{\partial D(i)} = \frac{\partial U\left(D(i)\right)}{\partial D_i(i)} - \pi_p - \pi_{MTP} = 0 \tag{18}$$

$$\frac{\partial U\left(D(i)\right)}{\partial D_i(i)} = \pi_p + \pi_{MTP} \tag{19}$$

The Taylor series expansion for customer's utility function can be written as Eq. (20).

$$\begin{aligned} &U\left(D(i)\right) = U\left(D_0(i)\right) + \frac{\partial U\left(D_0(i)\right)}{\partial D(i)} \Delta D_i + \\ &\frac{1}{2}\frac{\partial^2 U\left(D_0(i)\right)}{\partial D(i)^2} \left(\Delta D(i)\right)^2 \end{aligned} \tag{20}$$

The customer's benefit before implementing SEP contract can be represented as follows.

$$S_0 = U\left(D_0(i)\right) - D_0(i)\pi_0(i) \tag{21}$$

Thus,

$$\frac{\partial S_0}{\partial D(i)} = \frac{\partial U\left(D_0(i)\right)}{\partial D(i)} - \pi_0(i) = 0 \tag{22}$$

$$\frac{\partial U\left(D_0(i)\right)}{\partial D(i)} = \pi_0(i) \tag{23}$$

$$\begin{aligned} &\frac{\partial^2 U\left(D_0(i)\right)}{\partial D(i)^2} = \frac{\partial \pi(i)}{\partial D(i)} = \\ &\frac{1}{\varepsilon\left(i,\ i\right)} \frac{\pi_0(i)}{D_0(i)} \end{aligned} \tag{24}$$

Substituting Eqs. (23) and (24) in Eq. (20) results in obtaining the customer's utility function as follows.

$$\begin{aligned} &U\left(D(i)\right) = U\left(D_0(i)\right) + \pi_0(i)\Delta D(i) + \\ &\frac{1}{2\varepsilon\left(i,\ i\right)} \frac{\pi_0(i)}{D_0(i)} \left(\Delta D(i)\right)^2 \end{aligned} \tag{25}$$

$$\begin{aligned} &\frac{\partial U\left(D(i)\right)}{\partial D(i)} = \pi_0(i) + \\ &\frac{1}{\varepsilon\left(i,\ i\right)} \frac{\pi_0(i)}{D_0(i)} \left(\Delta D(i)\right) \end{aligned} \tag{26}$$

Therefore, the customer's consumption after selecting the MTP can be represented as follows by comparing Eqs. (19) and (26).

$$D(i) = D_0(i) \left(1 + \frac{\pi_p + [\pi_{MTP} - \pi_0(i)]}{\pi_0(i)} \varepsilon(i,j)\right) \tag{27}$$

Table 3. Comparing different electricity pricing method.

	FPT	**RTP**	**SEP**
Market price risk for customer	None	High	Selective
Market price volatility	High	Relatively low	Depends on the customers' selection
Average of customers' payment	Relatively high	Relatively low	Selective

The above-mentioned equations are written as follows when the market price is less than the predetermined MTP.

$$S = U(D(i)) - \pi(i)D(i) - \pi_p D(i) \tag{28}$$

$$\frac{\partial U(D(i))}{\partial D(i)} = \pi_p + \pi(i) \tag{29}$$

$$D(i) = D_0(i)(1 + \frac{\pi_p + [\pi(i) - \pi_o(i)]}{\pi_0(i)}\varepsilon(i,i) \tag{30}$$

Thus, the electricity demand is calculated as follows.

$$\begin{cases} D(i)=D_0(i)(1+\frac{\pi_p+[\pi(i)-\pi_o(i)]}{\pi_o(i)}\varepsilon(i,i)) & if\ \pi(i)\leqslant\pi_{MTP} \\ D(i)=D_0(i)(1+\frac{\pi_p+[\pi_{MTP}-\pi_o(i)]}{\pi_o(i))}\varepsilon(i,i)) & if\ \pi(i)>\pi_{MTP} \end{cases} \tag{31}$$

Based on Eq. (31), the customer is less motivated to adopt his/her consumption by market price when he/she selects the lower MTP. An increase in the MTP level decreases the motivation due to the moral hazards [47].

3.2. Effect of SEP on demand in multi-period

The demand changing in response to the market price variation considering cross elasticity is as follows.

$$S = \sum_{j=1}^{24} U(D(j)) - \pi(j)D(j) - \pi_P D(j) + (\pi(j) - \pi_{MTP})\, D(j) \tag{32}$$

$$\frac{\partial S}{\partial D(i)} = \frac{\partial U(D(i))}{\partial D(i)} - \sum_{j=1}^{24} \pi_p(j) + \pi_{MTP}(j)\frac{\partial D(j)}{\partial D(i)} = 0 \tag{33}$$

$$S_0 = \sum_{j=1}^{24} U(D_0(j)) - \pi_0(j)D_0(j) \tag{34}$$

$$\frac{\partial S_0}{\partial D_0(i)} = \frac{\partial U(D_0(i))}{\partial D_0(i)} - \sum_{j=1}^{24} \pi_0(j)\frac{\partial D_0(j)}{\partial D_0(i)} = 0 \tag{35}$$

$$D(i) = D_0(i) + D_0(i)\frac{\pi_p + \pi(i) - \pi_0(i)}{\pi_0(i)}\varepsilon(i,i) + \sum_{\substack{j=1 \\ j\neq 1}}^{24} D_0(j)\frac{\pi_p + \pi(j) - \pi_0(j)}{\pi_0(i)}E(j,i) \tag{36}$$

$$\begin{cases} D(i)=D_0(i)+\sum_{j=1}^{24} D_0(j)\frac{\pi_p+(\pi(j)-\pi_o(j))}{\pi_o(i)}\varepsilon(j,i) & if\ \pi(j)\leqslant\pi_{MTP} \\ D(i)=D_0(i)+\sum_{j=1}^{24} D_0(j)\frac{\pi_p+(\pi_{MTP}-\pi_0(j))}{\pi_0(i))}\varepsilon(j,i) & if\ \pi(j)>\pi_{MTP} \end{cases} \tag{37}$$

The following equation describes the relationship between the risk aversion coefficient and price elasticity of electricity demand under the exponential utility function.

$$\varepsilon(i,i) = \frac{-1}{r(i)D_0(i)} \tag{38}$$

$$\varepsilon(i,j) = \frac{1}{r(i)D_0(i)}\frac{[1 - r(j)D_0(j)]}{\sum_{k=1}^{T}\frac{\pi_0(k)}{\pi_0(j)}\frac{r(j)}{r(k)}} \tag{39}$$

Based on Eqs. (31) and (39), electricity energy consumption is related to the selected MTP level. In addition, the wholesale market price is related to the amount of electrical energy consumption. The weighted average price index is utilized here based on Eq. (40) to measure the impact of the selected MTP on the wholesale market price.

$$\mu(\pi_{\text{MTP}}) = \frac{\sum_{i=1}^{T} \pi_{\pi_{MTP}}(i) \times D_{\pi_{MTP}}(i)}{\sum_{t=1}^{T} D_{\pi_{MTP}}(i)} \tag{40}$$

where $\pi_{\pi_{MTP}}(i)$ and $D_{\pi_{MTP}}(i)$ represent the wholesale market price and system load hypothesis, respectively. All of the customers select π_{MTP} at i^{th} time period.

Electricity retailer receives premium to reimburse market price risk which is related to the selected MTP. The retailer should pay high reimbursement and vice versa when the customer selects low MTP. In fact, the market and customer benefit by reducing the average market price and selecting high MTP. Thus, market benefit function evaluates the value of the contract as Eq. (41). Eq. (42) is applied to determine the SEP contract premium (π_P^+) which is related to the market benefit function, expected reimbursement, and premium loading coefficient (k). This coefficient is designed to compensate designing and implementing cost of different SEP contracts providing for the retailer. In addition, SEP reimbursement (Re) is related to the market price and MTP level as Eq. (43).

$$\xi(\pi_{\text{MTP}}) = \frac{\mu(\pi_{\text{MTP}}) - \mu(\pi_{\text{RTP}})}{\mu(\pi_{\text{FTP}}) - \mu(\pi_{\text{RTP}})} \tag{41}$$

$$\pi_P^+(\pi_{\text{MTP}}) = (1 + K) \times E\left[\text{Re}(\pi_{\text{MTP}})\right] \times \xi(\pi_{\text{MTP}}) \tag{42}$$

$$\text{Re}(\pi_{\text{MTP}}) = \begin{cases} \pi\left(t\right) - \pi_{\text{MTP}} & \pi\left(t\right) > \pi_{\text{MTP}} \\ 0 & \pi\left(t\right) \leqslant \pi_{\text{MTP}} \end{cases} \tag{43}$$

To determine premium loading level optimally, the retailer maximize his/her profit based on the following equation.

$$\text{Profit:T} \times \sum_{n=1}^{N} \pi_P^+(n) - \sum_{t=1}^{T}\sum_{n=i}^{N} \text{Re}(n,i) \tag{44}$$

where n is regarded as the customer type indices.

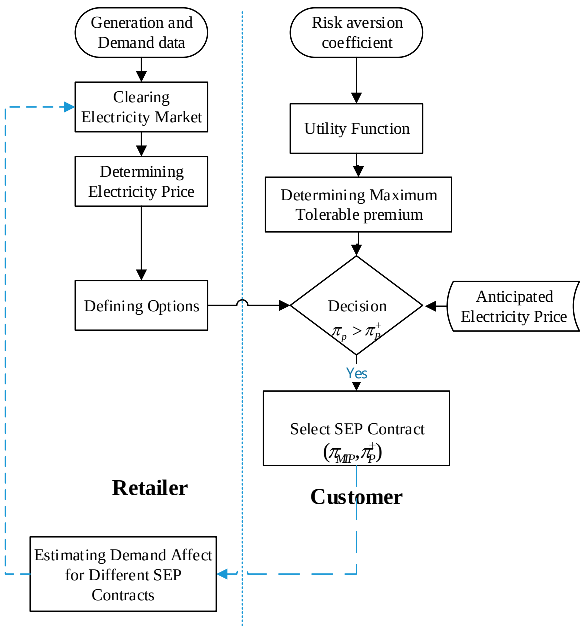

Fig. 5. Flowchart related to the proposed SEP.

Fig. 5 demonstrates the flowchart related to the proposed SEP from the viewpoint of consumers and retailer. Each customer has a view on the risk hedging premium based on his/her risk aversion behavior and prediction of the electricity market price. In addition, electricity retailer provides a table of different SEP contracts in which each contract is characterized by two main parameters including the maximum tolerable price and corresponding contract premium. Electricity retailer considers market benefit function of different contracts to specify the aforementioned parameters. Finally, the customer compares the contracts and select one which maximizes his/her benefit function.

4. Results

The proposed SEP was tested on 24-bus IEEE reliability test system (RTS) and the market clearing procedure employed in [48] was solved to determine electricity market price. Tables 4 and 5 show the system demand and generation bidding data of the selected system taken from [49].

The following hypotheses were considered to implement the proposed SEP.

- Retailer knows generations, demands, and network data adequately.
- Customers behave rationally and select a MTP based on their risk aversion behavior.
- Load is divided equally between four customer types (with risk aversion coefficients $r_1 = 0.1$, $r_2 = 0.2$, $r_3 = 0.3$, and $r_4 = 0.4$).

To evaluate different MTP effects, demand curves were simulated for different MTPs such as 0 (FPT), 10, 15, 20, 25, and 30$ (RTP). As displayed in Fig. 6, more demand is affected by decreasing the MTP level. As shown, electricity demand increases in the peak hours by implementing SEP since market price risk is relieved to

Table 4. Electricity demand for different hours.

Hour	Demand (MW)	Hour	Demand (MW)	Hour	Demand (MW)
1	2105	9	3190	17	3182
2	1979	10	3247	18	3421
3	1785	11	3247	19	3421
4	1755	12	3190	20	3247
5	1755	13	3109	21	3056
6	1785	14	3109	22	2787
7	2325	15	3123	23	2402
8	2829	16	3123	24	1979

Table 5. Bidding data of generation units.

Generation unit (MW)	Price ($)	Generation unit (MW)	Price ($)
400	5	76	21
350	8	50	0
197	9	20	23
155	12	12	27
100	17	-	-

the customers. In addition, the demand decreases in the off-peak because customer payment increases by adding the risk hedging premium.

Fig. 7 shows the customers' variable payment based on different MTP. Total customers' payment to the electricity energy is achieved by adding premium payments to these data (Fig. 8). The customer exposes to RTP and market price directly when he/she selects 30$ as the MTP. Further, the customer purchases electricity energy by FPT when he/she selects 0$.

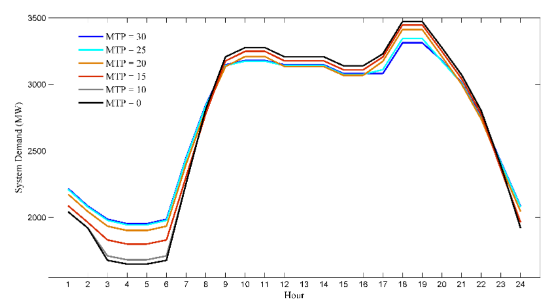

Fig. 6. System demand for various MTPs.

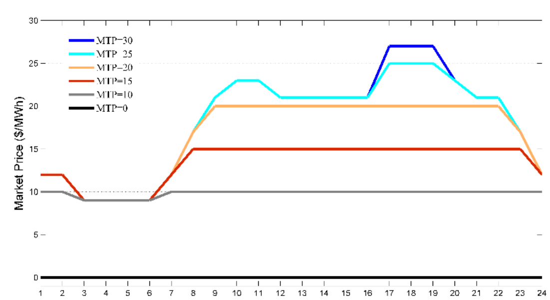

Fig. 7. Market variable price curves for various MTPs.

The maximum tolerable premium was calculated by the proposed procedure considering various risk aversion behaviors (Table 6). The customer exhibits more enthusiasm to accept SEP with the high premium level by increasing his/her risk aversion behavior. As observed, an increase in the MTP level decreases the premium.

Fig. 9 presents a comparative analysis of weighted average prices across different MTPs. A clear downward trend is evident, indicating that as the MTP value increases, the corresponding

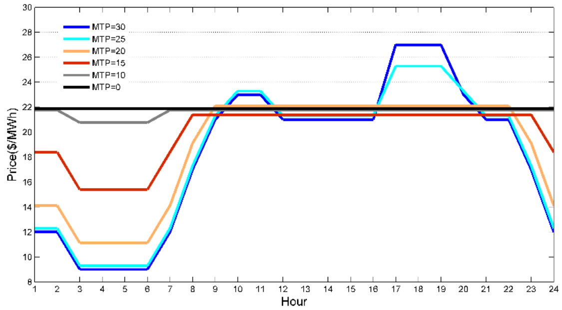

Fig. 8. Customer's total payment for various MTPs.

Table 6. Maximum tolerable premium for different risk aversion coefficients.

Risk aversion coefficient	Selected MTP ($)					
	0	10	15	20	25	30
0.1	20.04	10.0	5.56	1.66	0.27	0
0.2	21.9	11.7	6.23	1.74	0.29	0
0.3	23.8	13.5	7.29	1.82	0.32	0
0.4	25.6	15.2	8.15	1.89	0.34	0

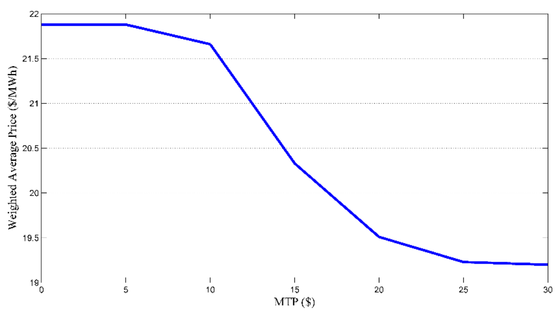

Fig. 9. Weighted average price for various MTPs.

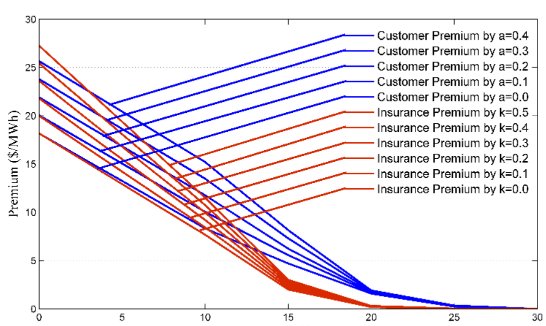

Fig. 10. Customers tolerable and contract premium for various MTPs considering different premium loading.

weighted average price tends to decrease. This phenomenon is particularly pronounced when contrasting the extremes: the highest weighted average price is observed for electricity energy sold under the Fixed Price Tariff FPT model, while the lowest is associated with the RTP model. These findings strongly suggest that from a market perspective, opting for higher MTP values is advantageous due to the potential for lower electricity costs. The retailer designs various SEP contracts and each customer compares these contracts with his/her risk aversion behavior. The customer selects a contract with the lowest MTP when his/her maximum tolerable premium is higher than the contract premium. Fig. 10 demonstrates the

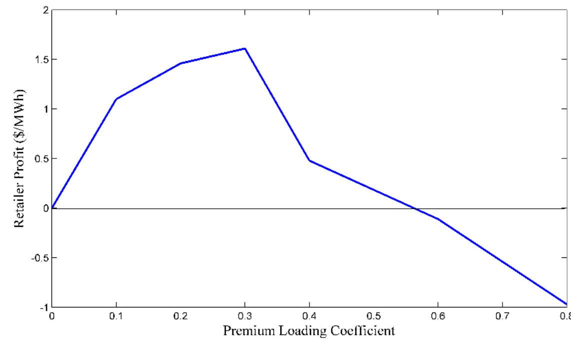

Fig. 11. Retailer profit per MW for different premium loading selection.

Table 7. Summary of SEP implementation.

Total premium	2879640$
Total reimbursement	2797550$
Demand reduction	2217MW
Electricity price increasing	0.46$/MW

customers' tolerable and contract premium by considering different premium loading levels. When the retailer implements a premium loading level of zero, a consistent pattern emerges: all customers unanimously opt for a MTP of $0. However, as the premium loading level is escalated, a corresponding increase in the selected MTP values by customers is observed. This empirical evidence suggests that the optimal MTP is a subjective determination contingent upon individual customer preferences and perspectives, necessitating a tailored approach to meet diverse customer needs.

Fig. 11 displays retailer profit per MW for different premium loading selection. The retailer's profit increases at first and then decreases when premium loading rises. Therefore, the optimal level of this coefficient is determined by 0.3.

Table 7 represents the summary of the proposed SEP implementation, indicating that the retailer can obtain 82090$ profit from the SEP implementation and average of the customers' payment. Additionally, the data shows that the demand increases by approximately $0.46 per MW and decreases by 2,217MW on average.

4.1. Flat-rate comparison

Selective electricity pricing, represents a significant improvement over flat-rate pricing models. While flat-rate structures maintain a constant per-unit cost regardless of market conditions, selective pricing dynamically adjusts rates based on real-time supply and demand. This allows the retailer to capture higher revenues during peak usage periods by raising prices, while also offering lower rates to incentivize off-peak consumption. The results demonstrate the advantages of this more sophisticated pricing strategy - the SEP model generated 17.27% higher profits for the retailer and reduced overall electricity demand by only 11.32%, compared to a 2,500MW drop under the flat-rate system. Importantly, SEP also enabled a 2.73% increase in the average customer payment, indicating consumers are willing to pay more for the benefits of dynamic pricing.

Table 8. Results of comparison.

Metric	Proposed SEP	Flat-rate pricing
Retailer profit	$82,090	$70,000
Avg. customer payment	$121.75	$118.50
Demand impact	Increase: $0.46/MW Decrease: 2,217MW	Increase: $0.30/MW Decrease: 2,500MW

5. CONCLUSION

A novel electricity pricing mechanism was developed by integrating fixed-price tariffs with dynamic pricing methods. Fixed-price tariffs sell electricity at a constant rate, regardless of market fluctuations. Dynamic pricing adjusts electricity prices based on system and market conditions. Despite its benefits, dynamic pricing has limited consumer adoption due to concerns over market price volatility. To address this, a risk-hedging mechanism was introduced, allowing consumers to set their Maximum Tolerable Price (MTP) based on their risk aversion. Retailers cover the difference between the market price and the MTP when prices rise, receiving a fixed hedging premium in return. The models developed calculate the maximum tolerable premium for each customer, considering risk aversion, demand elasticity, and consumption changes associated with the chosen hedging level. Results show that customers with low risk aversion prefer dynamic pricing, while those with high risk aversion pay a higher premium for price protection and select a lower MTP. Higher MTP values lead to greater load shifting from peak to off-peak hours, reducing market price fluctuations. The proposed mechanism offers several advantages, including customer choice of pricing plans, retailer profit, reduced load curve fluctuations, and decreased market price volatility.

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