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Research Article

Enhancing Peak Shaving through Nonlinear Incentive-Based Demand Response: A Consumer-Centric Utility Optimization Approach

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This paper presents a comparative study on the implementation of incentive-based demand response programs in power grid management, comparing the results obtained from linear and nonlinear models. The challenges faced by power grids in balancing supply and demand and managing price spikes during peak periods are addressed, and demand response programs are proposed as an effective strategy. The focus is on implementing incentive-based programs where load serving entities determine the optimal incentive price and demand reduction. A novel approach is presented for simulating consumer behavior based on the price elasticity of demand and consumers' utility function, incorporating both linear and nonlinear economic models. The calculation of demand reduction aims to maximize consumers' welfare, while the determination of the optimal incentive price maximizes the profit of the load serving entities. Real data are utilized, and the proposed models are implemented using the mixed-integer nonlinear programming (MINLP) method. The results demonstrate the effectiveness of providing incentives to consumers during peak hours compared to other approaches, with a comparison between the linear and nonlinear models.

1. Introduction

1.1. Motivation and Incitement. The smart grid has become an important part of modern society and the economy by increasing the interconnection of electricity with other sectors, including transportation, communication, and distributed energy resources (DERs) [1]. The integration of DERs has revolutionized the energy infrastructure, offering a sustainable and cost-effective solution to replace fossil fuel-based generation and enabling decentralized networks [2]. One critical distributed resource is demand response programs (DRPs), which balance supply and demand without changing power generation. DRPs incentivize changes in electricity usage patterns, reducing operating costs, greenhouse gas emissions, improving grid efficiency, and defending against cyberattacks such as false data injection (FDIA) [3–6].

With two-way communication, smart meters, and home energy management systems (HEMS), optimal demand-side planning and management are considered suitable solutions for implementing DRPs [3]. By exchanging data with consumers, power companies can implement DRPs, reducing the need for additional generation and transmission capacity expansion [8]. Such programs can also help facilitate retail choice and promote competition, ultimately leading to lower energy costs and prices that more closely reflect those of a free market [9–11].

However, implementing DRPs requires investment from various stakeholders. Consumers bear costs such as installing smart meters, telecommunications infrastructure, peak load control, HEMS, and investing in renewable energy. They are also responsible for operation and maintenance costs [6]. Meanwhile, system operators or service providers should pay for training consumers and telecommunications infrastructure on the control side, among others [12].

In summary, the shift towards DERs and DRPs offers limitless potential for reshaping the energy landscape and creating a sustainable energy system that is environmentally friendly and economically viable. However, it requires investment from various stakeholders, and careful planning and management are necessary to ensure efficient implementation.

Generally, DRPs are divided into two basic categories: price-based demand response programs (PBDRPs) and incentive-based demand response programs (IBDRPs). PBDRP offers the same price rate over a time period for all consumers with different consumption levels, which is one of its disadvantages [13, 14].

As a fundamental part, IBDRPs play a significant role in improving network performance, system reliability, and cost management. These programs aim to reduce consumer demand in response to price spikes, emergencies that threaten grid reliability, or critical peak hours [13, 14]. Unlike the PBPRP, these programs provide more flexibility for electric utilities to access responsive resources in addition to paying incentives to consumers instead of paying electricity bills at different prices during the day [14]. Moreover, these programs are more attractive to consumers than PBDRPs because people are motivated to accept an incentive program to receive more encouragement [15]. However, IBDRPs account for about 93% of peak demand reduction for available resources in the United States [16].

Today, in a competitive electricity market, the load serving entity (LSE) plays a critical role in establishing a link between wholesale markets and retail consumers to connect to an optimal operating framework. Their purpose in establishing this connection is to maximize their profit based on the uncertainties such as the electricity price and the consumer's demand [17]. The LSE participates in wholesale markets such as the real-time market and buys electricity at variable wholesale prices for retail consumers such as residential and small business consumers. Then, retail price signals are sent to consumers' smart meters through the advanced metering infrastructure (AMI) [18]. After receiving the price and establishing two-way communication between HEMS and the smart meter, HEMS controls the demand consumption of controllable appliances during peak hours by moving, disconnecting, or reducing the demand for these devices. This causes consumers' electric utilities cost reduction [19].

These programs must be optimally implemented to take full advantage of the potential of IBDRPs. Therefore, the problems in this field can be designed as an optimization of IBDRP implementation by the LSE.

1.2. Literature Review. It is evident that IBDRPs play a fundamental role in balancing electricity supply and demand. The implementation of these programs has been shown to offer benefits such as reducing greenhouse gas emissions, preventing or postponing costs associated with investment in the generation, transmission, and distribution sectors, and reducing consumer bill payments. However, there are challenges in optimizing IBDR, such as minimizing peak demand during critical periods while maximizing the profit of the LSE. Various researchers have proposed different IBDR models with different features and goals, including three-level hierarchical models, consumption management contracts, and interruptible load program models. Although some of these models have been criticized due to their assumptions or potential negative consequences, they hold promising potential in mitigating the challenges faced by the electricity market today, such as renewable energy uncertainty and price spikes.

Yu and Hong propose a three-level hierarchical model for IBDR that includes a system operator, aggregator, and consumer level. The model incentivizes the aggregator to implement IBDR on consumers by offering them a payment. Once motivated, the aggregator acts as an intermediary and reduces consumers' demand to maximize their own profit from exchanging DR with the system operator while minimizing consumers' incentive payments [20]. Pratik and Debapriya discuss new approach to managing energy in microgrids. The approach involves using both an IBDRP and a reconfiguration method to minimize costs and maximize profits for the microgrid operator. However, the reduction of energy demand resulting from DR programs can cause discomfort for consumers, which is modeled in terms of cost [21]. Additionally, Yu et al. introduce an IBDRP that allows consumers to reduce their demand in exchange for incentives that can be used as capacity resources in the wholesale market [22]. Consumers are incentivized to reduce their demand only if the aggregator calls upon them; otherwise, they face heavy penalties. Asadinejad et al. designed the IBDR model to address the negative impact of high price fluctuations on consumer satisfaction, LSE profit, and overall stress on the power system. The model calculates the optimal incentive price to encourage consumers to change their consumption patterns to prevent market price fluctuations. This model assumes a fixed incentive price of \$10/MWh higher than the fixed retail price and a linear relationship between the reduction in load and the incentive price [23]. Asadinejad and Tomsovic aimed to maximize LSE profit and designed an optimal DR plan using TOU and IBDR based on price elasticity to reduce the optimal demand during times where wholesale price increases above retail price. In the IBDR section, they consider a linear relationship between load reduction and incentive price [16]. Chai et al. present an IBDR model that maximizes retailers' profits during price spikes and peak consumption time by considering the consumer utility function and demand price elasticity. The model determines the optimal demand reduction by solving the consumer profit optimization model and fixing a certain incentive price. The optimal incentive price is then calculated by using the result of optimal demand reduction in the retailer's profit function and examining the effect of the incentive price on the retailer's profit [11]. Wang et al. proposed a two-level hierarchical model that uses controllable thermal loads, such as heating and air conditioning systems, as flexible sources for IBDR.

The system operator determines the incentive received by the aggregator for reducing the load. The aggregator then maximizes its profit from the revenue received from the system operator and the consumer's payment [24]. Salah et al. suggested an optimization model to calculate the optimal incentive price offered to consumers for their participation in IBDRP. This model is designed based on the consumers' behavior and preferences in response to the IBDR implementation. Finally, the LSE pays the incentive price set by the IBDR implementation model to the consumers to maximize the total LSE profit [25]. Muthirayan et al. designed an IBDR mechanism for balancing supply and demand during high price periods. The system operator recruits DR providers, who are either individual consumers or aggregators of DR services, to reduce load when the market price exceeds a threshold market clearing (TMC) price. The proposed DR mechanism involves self-reported baseline, randomized selection, and penalty for uninstructed deviations, with predetermined incentives for consumers. The mechanism controls baseline inflation for a quadratic utility function and significantly reduces SO costs. The self-reported baseline approach is more cost-effective than conventional methods, despite concerns about fatigue and lack of knowledge [26]. Chaman Lal et al. proposed a decentralized scheme for real-time IBDR using HEMS scheduling. It presents algorithms to increase flexibility, reduce errors, and ensure fairness for participants. Real-time IBDR is essential for managing power balance during uncertain scenarios. The paper discusses a three-level framework for implementing demand response and analyzes the impact of HEMS on real-time IBDR [27]. Malehmirchegini and Farzaneh suggested a multiobjective mathematical modeling approach to determine the optimal incentive rates for customers (CUs) participating in IBDRPs, taking into account price elasticity of demand and day-ahead wholesale electricity market price. The social aspect of IBDRP participation is also addressed by estimating CUs' satisfaction level with respect to four attributes: comfort, flexibility, energy security, and environmental protection, using the Kano model [28]. This paper introduces a novel incentive-based demand response scheme for electricity markets, addressing the challenges of future energy grids. The scheme facilitates energy trading between a service provider and customers, with the provider acting as a price maker by selling capacity resources obtained from consumers in exchange for demand reductions. Through optimization using GAMS and NLP, the scheme achieves significant demand reduction during high-priced peak periods. Deepan et al. introduced a novel incentive-based demand response (DR) program using a self-reported baseline mechanism. Consumers report their baseline, and during DR events, a random selection of consumers achieves the required load reduction. Those who comply are rewarded, while deviations from the baseline are penalized to control inflation. The selection probability can optimize the system operator's cost, resulting in a cost-effective design. Fu et al. proposed a bilevel bidding model for electricity retail companies to maximize profits while accounting for demand response uncertainty. The model incorporates price-based and incentive-based demand response, enabling companies to determine optimal bidding strategies, including prices and capacities, to achieve maximum profit and mitigate energy price volatility [29]. Gul and Suchitra presented a novel incentive-based demand response scheme. The scheme involves a service provider acting as a price maker and selling capacity resources obtained from consumers through demand reductions to the wholesale market. Consumers provide demand reductions in exchange for incentives. The interaction between the service provider and consumers is formulated as optimization problems solved using GAMS with nonlinear programming. The approach focuses on reducing demand during peak periods when energy prices are high [30]. Rana et al. focused on the efficient management of electricity grids through demand response (DR) programs, specifically in the context of a community microgrid (CMG). The study considers an incentive-based DR model where an aggregator provides flexibility to the CMG. The objective is to minimize the cost of flexibility management, which includes incentives for shifting demands and penalty payments for contractual violations. To achieve this, a two-stage optimization approach is adopted, utilizing a biobjective formulation followed by a single objective formulation [31]. Fotouhi Ghazvini et al. aimed to maximize the daily profit of the LSE while minimizing peak demand to avoid electricity purchases during market risk times [32]. To achieve this, the LSE calculated the optimal hourly incentive price for residential consumers based on generation capacity. However, the effect of distribution system operators on designing the optimal incentive price was not considered in their study. Currently, the electricity market faces two significant challenges: the entry of expensive power plants into the grid during peak hours and renewable energy uncertainty, which can cause wholesale prices to soar above retail prices. This price spikes poses financial risks to both LSEs and consumers and threatens the power grid's reliability. To mitigate these issues, Vu et al. proposed an IBDR model to minimize LSEs' financial losses during peak hours [33]. The IBDRP incentivizes consumers to reduce their energy consumption during peak hours below their baseline demand response level by offering incentives. The model utilizes a linear approach to optimize the problem and accounts for limited consumer response related to the IBDR implementation.

Numerous studies have been performed on different models of IBDR to determine the optimal incentive price and load reduction, as well as the impact of these programs on consumer behavior and LSE profit. The novelty of this paper lies in proposing nonlinear economic voluntary incentive models that consider the effect of the incentive price paid on electricity consumption to maximize the welfare of consumers participating in IBDR. In most cited papers such as [34], the relationship between incentive price and optimal load reduction is assumed linear. However, residential electricity consumption is variable and dependent upon consumer behavior, which plays a significant role in energy consumption [35]. Therefore, understanding consumer behavior and determining the appropriate incentive price to encourage consumers to participate in the program is particularly essential [36]. By utilizing these models, it is possible to find the best balance between incentivizing consumers to participate and maximizing the LSE's profits. Overall, this paper presents a novel approach by considering consumer behavior to develop an effective incentive model for IBDR programs that can both maximize consumer welfare and LSE profits.

1.3. Contribution and Paper Organization. The goal of this study is to propose an effective incentive pricing scheme for managing residential and small business sector electricity consumption in response to price spikes, emergencies, or peak demand, while ensuring the welfare of consumers.

The contributions of this paper are outlined below in a bulleted format.

(i) A nonlinear IBDR model is extracted from consumers' utility functions based on the effect of consumer behavior on electricity consumption
(ii) An optimization algorithm is developed to minimize consumer costs and maximize utility profits, ensuring a mutually beneficial outcome
(iii) Variable optimal incentives are determined based on factors such as the wholesale price, system operator price, and the level of IBDR implementation
(iv) Emphasis is placed on the coordination between the utility and system operator to ensure the reliability of the system
(v) Finally, this scheme provides a structured framework for retailers to select the most appropriate regions for IBDR implementation, resulting in better decision-making and optimized resource allocation

These contributions put forth an effective and holistic approach to managing residential and small business sector electricity consumption, which can benefit both the utility company and its consumers.

This paper is divided into five main sections as follows. Section 2 presents nonlinear economic load models based on utility functions. In Section 3, the LSE profit function, considering nonlinear models, is demonstrated. Simulation results are presented and discussed in Section 4. Finally, conclusion points are drawn in Section 5.

2. Demand Response in the IBDR Model

The problem and studied system are presented in this section. This paper aims for reducing consumer demand by developing the optimal incentive price in critical times. In the power system, each consumer has independent behavior, and their energy demand depends on various parameters, including their priorities, weather conditions, and electricity prices. For this reason, a proper understanding of consumer behavior and how consumers respond can help to develop DR programs [32, 33].

Consumer utility functions are used to model the impact of consumers' behavior on the implementation of the program. According to this function, linear and nonlinear economic voluntary incentive models were extracted as a function of consumer behavior to determine the effect of the incentive price on electricity consumption. Based on these derived economic models, voluntary incentive-based programs are proposed to maximize consumer welfare. Then, these models are used to find the optimal incentive price and load reduction by maximizing the LSE profit.

Four demand functions are illustrated in Table 1. The table provides the formula of some demand functions in terms of D and P (price and demand) for certain coefficients such as a and b.

A simple and low-accuracy method of analyzing consumer behavior and utility functions is the IBDR linear model. However, optimization problems in the power system and related constraints tend to be nonlinear. It is necessary to extract nonlinear models and compare their results to the linear model for the accuracy and efficiency of the IBDR model improvement. Due to this, exponential, logarithmic, and power nonlinear models are used. As a result, these functions are used more often because their formulas are simple to understand [37].

2.1. Deriving Exponential IBDR Model. In normal circumstances, consumers purchase their electricity at retail prices $P(t)$ from the LSE. According to the utility function $U(D(t), w)$ in Figure 1, the following equation is used to calculate consumers' profit $S(D(t), w)$ [38]:

$$S(D(t), w) = U(D(t), w) - P(t) \times D(t). \quad (1)$$

By implementing IBDR during peak periods and price spikes, consumers can reduce their consumption $\Delta D(t)$ and receive rewards $P_{\text{inc}}(t)$. Therefore, the benefit function can be written as follows [33]:

$$S(D(t), w) = U(D(t), w) - P(t) \times D(t) + P_{\text{inc}}(t) \times \Delta D(t), \quad (2)$$

$$\Delta D(t) = D_0(t) - D(t). \quad (3)$$

To effectively model consumer behavior towards IBDR, maximizing consumer benefit is the key. This involves analyzing the multivariable function $S(D(t), w)$, where $D(t)$ represents electricity demand and w denotes consumer's willingness to their consumption. The ideal value of $D(t)$ that maximizes consumer benefit is determined by calculating the sensitivity of function S to changes in $D(t)$, while keeping other variables constant. This involves taking partial derivatives of the function with respect to $D(t)$ to assess their impact on consumer benefit. The analysis also considers the partial derivatives of the utility function and electricity demand, evaluating their collective influence on the overall change. By deriving the consumers' benefit function from $D(t)$ and considering these factors, we gain a comprehensive understanding of consumer behavior in relation to IBDR [38].

$$\frac{\partial S(D(t), w)}{\partial D(t)} = \frac{\partial U(D(t), w)}{\partial D(t)} - P(t) + \frac{P_{\text{inc}}(t) \times \partial(\Delta D(t))}{\partial D(t)} = 0. \quad (4)$$

Table 1: Linear or nonlinear demand functions.

Function	Formula
Linear	$D = a + b \times P$
Exponential	$D = a \times e^{b \times P}$
Logarithmic	$D = a_1 + a_2 \times \ln P^b$
Power	$D = a \times P^b$

Then, equation (4) is written as equation (5) after derivation and sorting in accordance with equation (2) [38].

$$\frac{\partial U(D(t), w)}{\partial D(t)} = P(t) + P_{\text{inc}}(t). \tag{5}$$

Various nonlinear functions are used to model consumer behavior, such as logarithmic, exponential, or quadratic functions. The Taylor series expansion is used for consumers' profit maximization [39]. Moreover, before the implementation of IBDR, the profit function is as follows [38]:

$$\begin{gathered} S(D_0(t), w) = U(D_0(t), w) - P_0(t) \times D_0(t), \\ \frac{\partial S(D_0(t), w)}{\partial D_0(t)} = \frac{\partial U(D_0(t), w)}{\partial D_0(t)} - P_0(t) = 0. \end{gathered} \tag{6}$$

The price elasticity of demand $E(t)$ shows the sensitivity of demand to price changes as shown following relationship [38]:

$$E(t) = \frac{\partial D(t)}{\partial P(t)} \times \frac{P_0(t)}{D_0(t)}. \tag{7}$$

Based on the exponential demand function of Table 1 and the second-order Taylor series expansion, the exponential model is written in the following form [37]:

$$U(D(t), w) = U(D_0(t), w) + P_0(t) \times D(t) \times \left\{1 + \frac{1}{E(t)}\left[\ln\left(\frac{D(t)}{D_0(t)}\right) - 1\right]\right\}. \tag{8}$$

Deriving from equation (8), we have the following equation:

$$\frac{\partial U(D(t), w)}{\partial D(t)} = P_0(t) \times \left\{1 + \frac{1}{E(t)}\left[\ln\left(\frac{D(t)}{D_0(t)}\right) - 1\right]\right\} + P_0(t) \times D(t) \times \left\{\frac{1}{E(t)} \times \frac{1}{D_0(t)} \times \frac{D_0(t)}{D(t)}\right\}. \tag{9}$$

In order to extract the exponential model of the incentive-based program, we put equation (5) in equation (9) and sort the formula, assuming the price remains constant before and after IBDR implementation ($P_0(t)$ and $P(t)$) and equals to $P_{\text{retail}}(t)$, as indicated by equation (11); the exponential IBDR model is obtained as follows:

$$P(t) = P_0(t) = P_{\text{retail}}(t), \tag{10}$$

$$D(t) = D_0(t) \times \text{EXP}\left\{E \times \frac{P(t) + P_{\text{inc}}(t) - P_0(t)}{P_0(t)}\right\}, \tag{11}$$

$$D(t) = D_0(t) \times \text{EXP}\left\{E \times \frac{P_{\text{inc}}(t)}{P_{\text{retail}}(t)}\right\}. \tag{12}$$

2.2. Deriving Logarithmic IBDR Model. Based on the assumptions related to the consumers' profit function and the demand function of Table 1, the logarithmic model can be represented as follows [37]:

$$\begin{aligned} U(D(t), w) &= U(D_0(t), w) + P_0(t) \times D_0(t) \\ &\quad \times E\left\{\text{EXP}\left[\left(\frac{D(t) - D_0(t)}{E \times D_0(t)}\right) - 1\right]\right\}. \end{aligned} \tag{13}$$

Derived from equations (13) and (14), the following equation is obtained [37]:

$$\frac{\partial U(D(t), w)}{\partial D(t)} = P_0(t) \times D_0(t) \times E \times \left(\frac{1}{E \times D_0(t)}\right) \times \text{EXP}\left(\frac{D(t) - D_0(t)}{E \times D_0(t)}\right). \tag{14}$$

According to the same process as in the previous model, the following equation is obtained:

$$D(t) = D_0(t)\left\{1 + E \times \ln\left(\frac{P_{\text{retail}}(t) + P_{\text{inc}}(t)}{P_{\text{retail}}(t)}\right)\right\}. \tag{15}$$

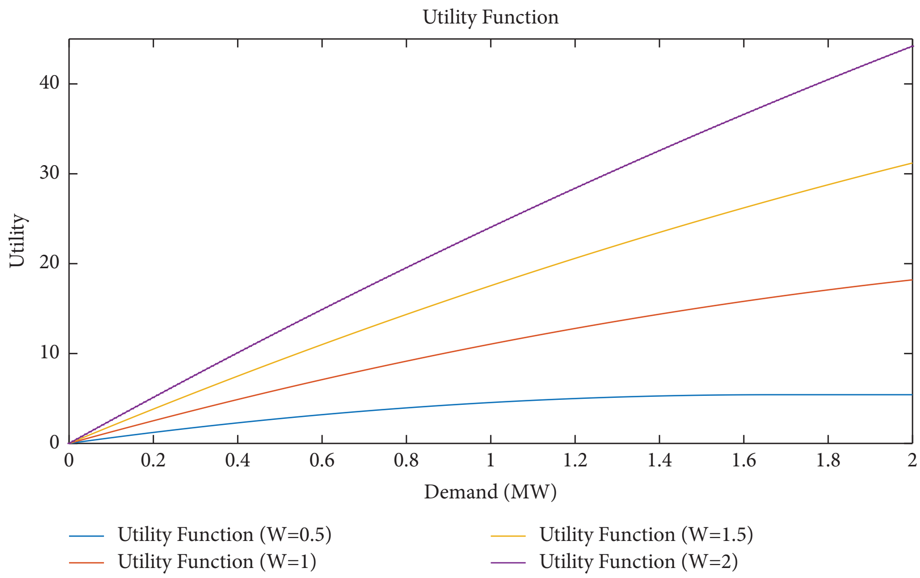

Figure 1: Utility function based on consumers' consumption.

2.3. Deriving Power IBDR Model. Utilizing the exponential function of the demand function and the work process as described in the previous two models, we achieve the following relations [37]:

$$U(D(t),w) = U(D_0(t),w) + \frac{P_0(t)\times D(t)}{1+E^{-1}} \times \left\{ \left(\frac{D(t)}{D_0(t)}\right)^{E^{-1}} - 1 \right\}, \tag{16}$$

$$\frac{\partial U(D(t),w)}{\partial D(t)} = \frac{P_0(t)}{1+E^{-1}} \times \left\{ \left(\frac{D(t)}{D_0(t)}\right)^{E^{-1}} - 1 \right\} + \frac{P_0(t)\times D(t)}{1+E^{-1}} \times \left\{ \frac{E^{-1}}{D_0(t)} \times \left(\frac{D(t)}{D_0(t)}\right)^{E^{-1}-1} \right\}, \tag{17}$$

$$\frac{P(t)+P_{\text{inc}}(t)}{P_0(t)} = \left(\frac{D(t)}{D_0(t)}\right)^{E^{-1}} - \left(\frac{1}{1+E^{-1}}\right). \tag{18}$$

For small demand elasticities and using assumption equation (10), the final power IBDR model is given by the following equation:

$$D(t) = D_0(t) \times \left(\frac{P_{\text{retail}}(t)+P_{\text{inc}}(t)}{P_{\text{retail}}(t)}\right)^{E}. \tag{19}$$

Figure 2 compares linear, exponential, logarithmic, and power models based on the changes in elasticity from 0 to −0.3. The power model experiences fewer load reductions than the others. Load reduction rates in the four models become similar at low elasticity values but diverge as elasticity increases. Also, the difference between the four curves is small since the Taylor expansion omits the second term due to the low elasticity in the four models.

3. Load Serving Entities' Profit

Usually, the wholesale price $P_{\text{wholesale}}(t)$ is lower than the retail price. Therefore, the LSE income is derived from the difference between the two prices. However, there are times when unexpected factors such as high demand (demand D_0 is more than supply D_s) or price spikes prevent the LSE from providing electricity to its consumers, resulting in outage costs. In this regard, the LSE cooperates with the system operator to implement IBDR and receives incentive price

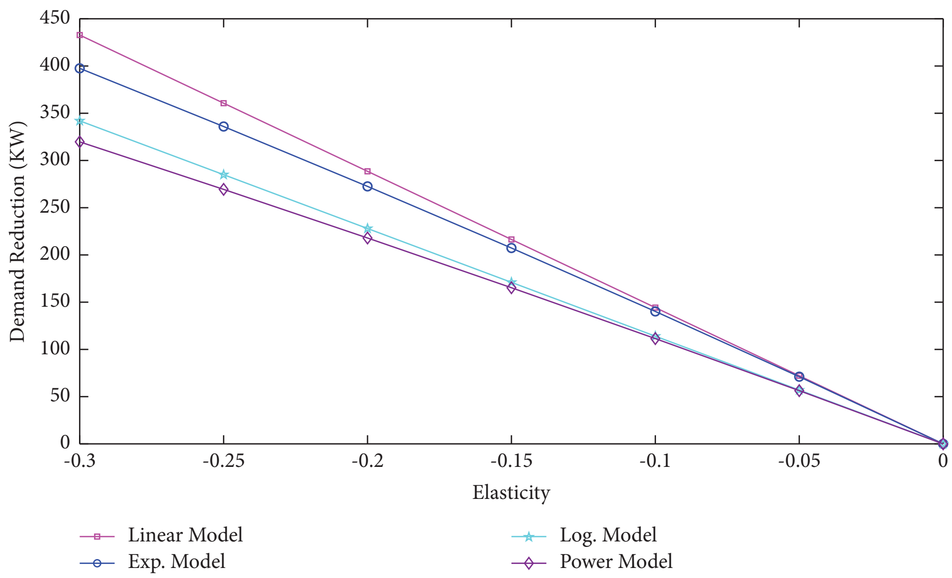

FIGURE 2: Comparison of 4 models based on elasticity change.

$P_{\text{dso}}(t)$. As a result, we assume that equation (20) represents the LSE's objective function:

$$\text{Profit}\begin{cases}\sum_{t=1}^{24} D_0(t)\times\left(P_{\text{retail}}(t)-P_{\text{wholesale}}(t)\right), & D_0 = D_s,\\ \sum_{t=1}^{24} D_0(t)\times\left(P_{\text{retail}}(t)-P_{\text{wholesale}}(t)\right)-\left(D_0-D_s\right)\times\text{outagecost}, & D_0 > D_s.\end{cases} \tag{20}$$

In the case of $D_0 = D_S$, the following profit function is obtained after IBDR implementation [11]:

$$\max\text{profit} = \sum_{t=1}^{24}\left(D_0(t)-\Delta D(t)\right)\times\left(P_{\text{retail}}(t)-P_{\text{wholesale}}(t)\right)+\Delta D(t)\times\left(P_{\text{dso}}(t)-P_{\text{inc}}(t)\right)$$
$$\begin{cases}P_{\text{inc}}\geq 0,\\ 0\leq\Delta D(t)\leq\Delta D_{\max}.\end{cases} \tag{21}$$

The flowchart of the proposed IBDR scheme is shown in Figure 3. In Figure 3, steps 1 and 2 are designed to derive a nonlinear IBDR scheme based on customer profit maximization, while steps 3 and 4 are presented to determine the optimum incentive price and load reduction by using MINLP method aimed at maximizing the LSE benefits during times of high demand or price spikes. The MINLP method helps identify the optimal combination of incentive price and load reduction to achieve this goal.

4. Simulation and Results

This paper focuses on the DPL area of the PJM market in the mid-eastern Atlantic region of the United States, where residential customers account for 46% of electricity consumption. The selected bus for analysis is BETHANY with identification number 49865, which is a load type with a voltage level of 69 kV and located in Bethany Beach (zip code 19930). This paper presents price and demand data

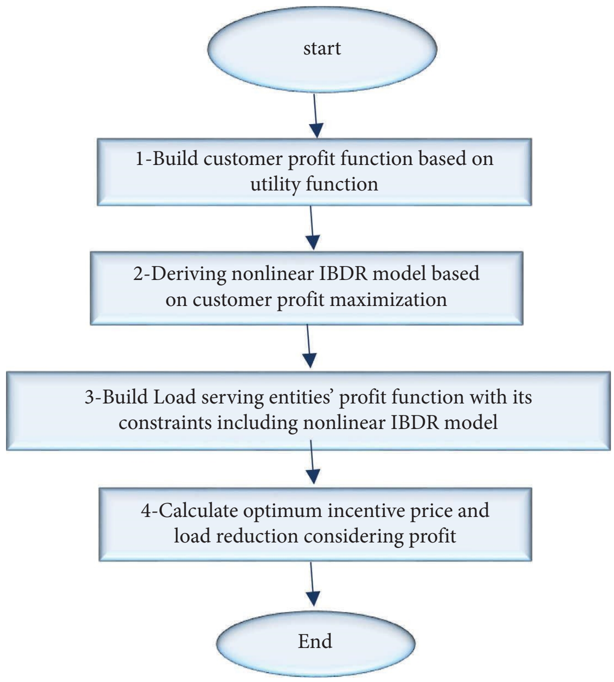

Figure 3: Flowchart of proposed IBDR scheme.

from a peak summer day in July 2020, with a particular emphasis on residential energy consumption (Figure 4) [40, 41]. Furthermore, it is essential to note that the considered demand is an aggregate of consumers' loads. Several LSEs in this area offer fixed-rate electricity plans for both the short and long term. Therefore, the estimated retail price is 69.9 \$/MWh [42]. In addition, the day is divided into three periods: midpeak, off-peak, and peak period. Therefore, the price elasticities of different types of demand are calculated for each of these periods (see Table 2) [39].

Some studies such as [16, 39] have examined the potential impact of implementing IBDR on reducing overall energy load. These studies suggest that such implementation could result in load reductions ranging from 10% to 40% compared to the baseline load.

To determine which devices to prioritize during power outages, consumer devices are usually categorized into four main groups: critical, interruptible, noninterruptible, and shiftable to off-peak and midpeak times. Further analysis can be conducted based on the operating time of these devices:

(1) Long operation period (3 hours or more): This category includes appliances such as refrigerators, TVs, computers, sound systems, lighting, and water heaters
(2) Medium operation period (between 1 and 3 hours): Appliances falling into this group typically include ovens, irons, vacuum cleaners, and dishwashers
(3) Short operating period (maximum 1 hour): Washing machines and electric kettles are examples of devices belonging to this group

By strategically disconnecting and transferring loads from devices such as washing machines, dryers, dishwashers, irons, vacuum cleaners, and pool pumps, and by reducing loads from devices such as water heaters and air conditioners, it becomes possible to achieve a significant load reduction of up to 30%.

In summary, the studies indicate that implementing IBDR can lead to substantial load reductions by categorizing devices based on their operating time and selectively managing their power consumption during periods of high demand or power outages.

Furthermore, GAMS software has been used to determine the optimal incentive price which is lower than the wholesale price and the amount of load reduction based on the LSE's objective function.

Eslaminia and Mashhadi [34] assumed a linear relationship between incentive price and load reduction. While linear modeling is easy to analyze, it lacks accuracy especially when dealing with nonlinear functions such as optimization in power systems and related constraints.

To improve the accuracy and efficiency of the model and its implementation on a real system, it is necessary to use nonlinear models. Therefore, this section presents the results of nonlinear modeling and compares them with those obtained from the linear model presented in paper [34]. By doing so, we aim to enhance the accuracy of the model and make it more suitable for practical applications.

Overall, this research highlights the importance of accurately modeling incentive-based programs for load reduction in power systems. The use of nonlinear models can significantly improve the accuracy of these programs and help ensure their effectiveness in practice. In order to validate the superiority of our proposed model, we have compared our calculations with another state-of-the-art existing scheme. Specifically, we compared our nonlinear modeling results with the linear model presented in paper [34]. Our results show that the nonlinear model outperforms the linear model in terms of accuracy and efficiency. Therefore, our proposed nonlinear model can be considered as a better option for practical applications.

4.1. Case 1: Not Receiving Incentives from the System Operator. In the first case, the analysis compares the results of the base case and of the linear and nonlinear models without considering the effect of the incentive price paid by the system operator. The focus is on the sensitivity of consumers to IBDRPs. The findings indicate that without incentives from the operator, there is a low load reduction percentage observed, suggesting low consumer sensitivity to IBDRPs. In this case, the assumption is made that the initial demand (D_0) is equal to the supply generated by power plants (D_s). This implies that at the beginning of the observed period or scenario, the total electricity demand matches the total supply available from power generation sources. The optimal incentive price and the demand reduction amount were then calculated assuming that the maximum demand reduction was equal to 15% of the initial demand.

During peak times, supplying consumers becomes a significant challenge. Therefore, demand reduction is of major importance for the system operator during these

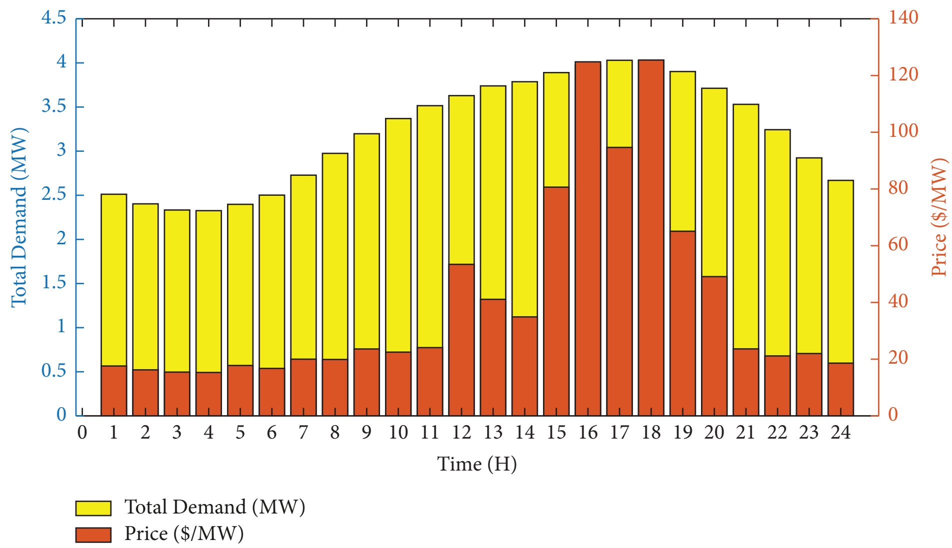

Figure 4: Total demand and $P_{\text{wholesale}}$.

Table 2: Price elasticity of demand [34].

Time	1 am–7 am	8 am–11 pm	12 pm–9 pm	10 pm–12 am
Price elasticity	−0.08	−0.11	−0.19	−0.11

times. As a result, the highest increase in profit and decrease in cost were observed in the linear model (Table 3). Additionally, the maximum load reduction occurred at 18:00 for all models, with the linear model achieving the greatest load reduction (the most optimistic state) while the power model experienced the least reduction (the most pessimistic or conservative model).

4.2. Case 2: Receiving Incentives from the System Operator. This case examines the impact of receiving incentives from the system operator on the profitability of the LSE and the costs borne by the company. High electricity prices during peak hours result in increased costs for the LSE, including outage costs. The LSE must purchase electricity at a higher price from the grid and sell it to consumers at a retail price. Additionally, the LSE incurs outage costs due to supply-demand imbalances, resulting in power cuts and an average payment of $1,000/MW for outage power. Consequently, the LSE's profit significantly declines, leading to substantial losses for the company. However, implementing IBDRPs with operator incentives can help address these challenges by reducing demand, preventing outages, and improving the LSE's profitability. The supply is assumed to be 15% lower than the initial demand from 12 to 8 pm. Hence, the LSE must cut the power and pay an average of $1,000/MW for outage power. After paying the outage cost, Table 4 shows that the LSE's profit has plummeted significantly, and the company burdens a huge loss.

In this case, it is assumed that the initial demand, denoted as $D_0(t)$, is equal to the supply generated by power plants, represented by D_s. Therefore, implementing IBDRPs can meet consumers' demand and prevent power outages and outage costs. It is assumed that the incentive price paid by the system operator is 1.5 times the wholesale market price, and the maximum load reduction is equal to 15% of the initial load. According to Figures 5 and 6, the incentives given by the operator increase the incentive price and reduce demand, proving the accuracy of the proposed models. Figures 5 and 6 validate the proposed models by demonstrating the impact of operator incentives on incentive price and demand. The figures show that offering incentives increases the incentive price and decreases demand. During peak hours, load reduction remains constant across all models due to maximum constraints, limiting further demand reductions. Additionally, the introduction of incentives from the operator significantly affects the LSE's profit and consumers' costs, with the LSE's profit increasing. Overall, the optimization models successfully maximize profit (Table 5).

4.3. Case 3: Increasing the Maximum Load Reduction Limit. In Case 3, increasing the maximum allowable load reduction limit has been performed to investigate the potential for additional demand reduction and its effects. The analysis shows that raising the maximum load reduction results in higher incentive prices and lower demand. It also emphasizes the connection between incentive prices, consumer satisfaction, and demand reduction. Therefore, the maximum load reduction is set at a fixed percentage of 30% of the initial load, with D_s being equal to D_0. Additionally, the system operator pays an incentive price assumed to be 1.5 times the wholesale price.

Table 3: The LSE profit and consumers' cost in case 1.

Model	Maximum percentage of demand reduction (%)	Decreasing the consumers' cost compared to the base case (%)	Consumers' cost ($)	Increasing the LSE profit compared to the base case (%)	The LSE profit ($)
Base case	—	—	5403.74	—	1937.5
Linear	7.94 at 6 pm	1.45	5325.53	1.01	1957.09
Exp	7.49 at 6 pm	1/37	5329.71	0.97	1956.39
Log	6.25 at 6 pm	1/16	5341.3	0.87	1954.28
Power	5.98 at 6 pm	1/11	5343.83	0.84	1953.8

Table 4: Comparison of LSE profit before and after charging outage costs.

Consumers' cost in base case ($)	Consumers' cost based on outage cost ($)	The LSE profit in base case ($)	The LSE profit based on outage cost ($)	Consumers' cost in base case ($)	Consumers' cost based on outage cost ($)
5403.74	201.41	1937.5	−3265.09	5403.74	201.41

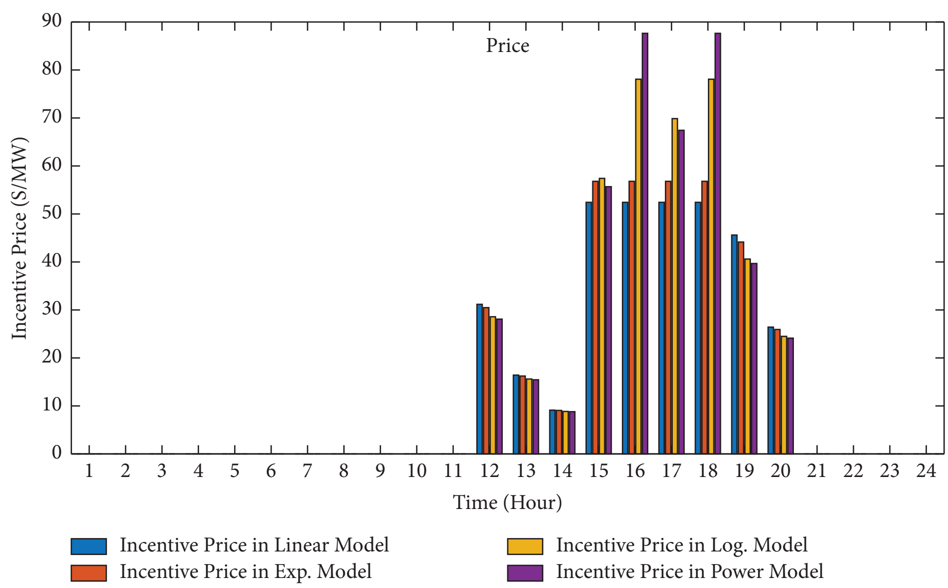

Figure 5: Optimal incentive price in case 2.

It can be seen from Figures 7 and 8 that reducing the maximum allowable load to 30% of the initial load resulted in a higher incentive price and a lower demand. In Table 6, the percentage of acceptable load reduction per model varies at 6 pm, depending on the demand reduction. Moreover, demand can be reduced by up to 30% to ensure consumer satisfaction. Based on the relationship between Figures 1 and 9, it can be inferred that as consumers reduce their load, their level of satisfaction and utility function decreases. This function reflects their satisfaction based on their electricity consumption. It is essential to observe Figure 9 to understand that higher incentive prices received by consumers during peak times, such as 6 A.M., result in greater demand reduction through the implementation of IBDRP. In other words, the higher the incentive price, the more willing consumers are to reduce their demand. Furthermore, curves for all the models overlap in the first 5% of the load reduction, but after that, they diverge, and their trends differ. In the long run, as consumption is reduced, people will show more resistance and require higher incentive prices. It is essential to note that the higher LSE profit observed in the linear model does not indicate its superiority over nonlinear models. The linear model assumes a linear relationship between incentives and consumption reduction, which is not realistic. In contrast, nonlinear models capture complexities and individual preferences better. Logarithmic and power models provide a better fit than linear models. The focus of this paper is on the practical applicability of nonlinear models in understanding incentivized energy consumption dynamics, rather than comparing LSE profits based on Table 6 alone. Using these models enhances decision-making processes in this field.

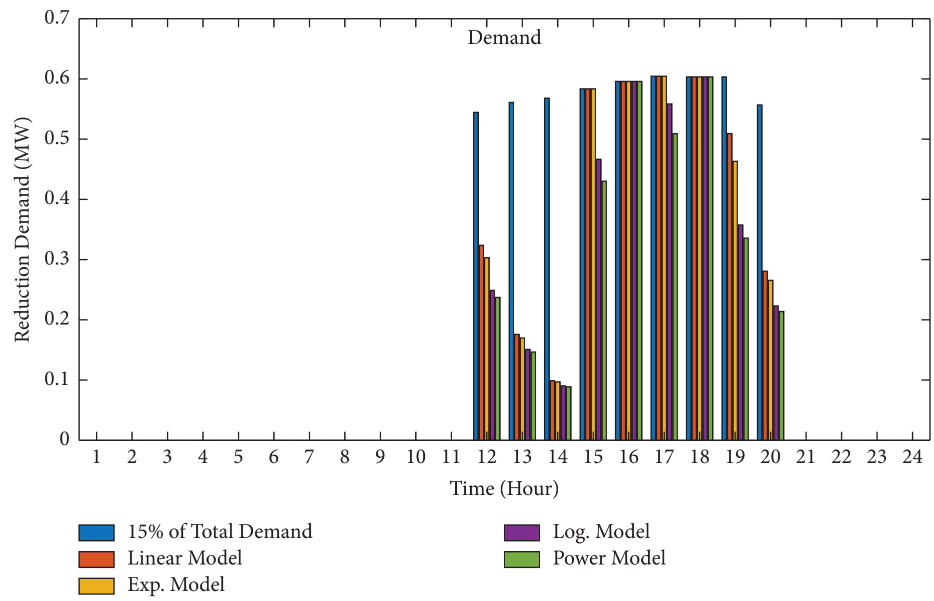

Figure 6: Demand reduction in case 2.

Table 5: The LSE profit and consumers' cost in case 2.

Model	Maximum percentage of demand reduction (%)	Decreasing the consumers' cost compared to the base case (%)	Consumers' cost (%)	Increasing the LSE profit compared to the base case (%)	The LSE profit ($)
Base case	—	—	5403.74	—	1937.5
Linear	15 at 3, 4, 5, and 6 pm	8.023	4970.19	20.10	2327.04
Exp	15 at 3, 4, 5, and 6 pm	8.02	4970.33	19.45	2314.38
Log	15 at 4 and 6 pm	7.77	4983.79	16.71	2261.17
Power	15 at 4 and 6 pm	7.63	4991.32	15.76	2242.82

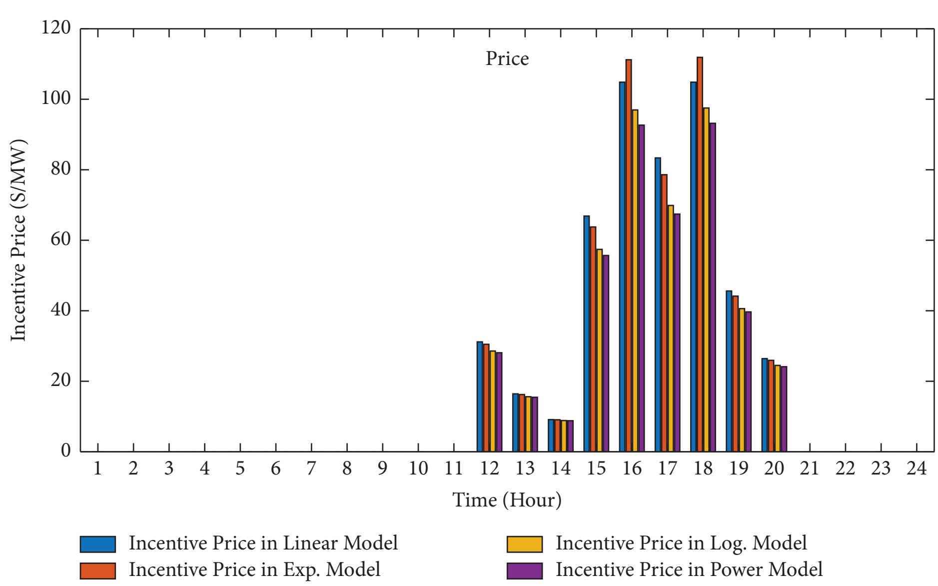

Figure 7: Optimal incentive price in case 3.

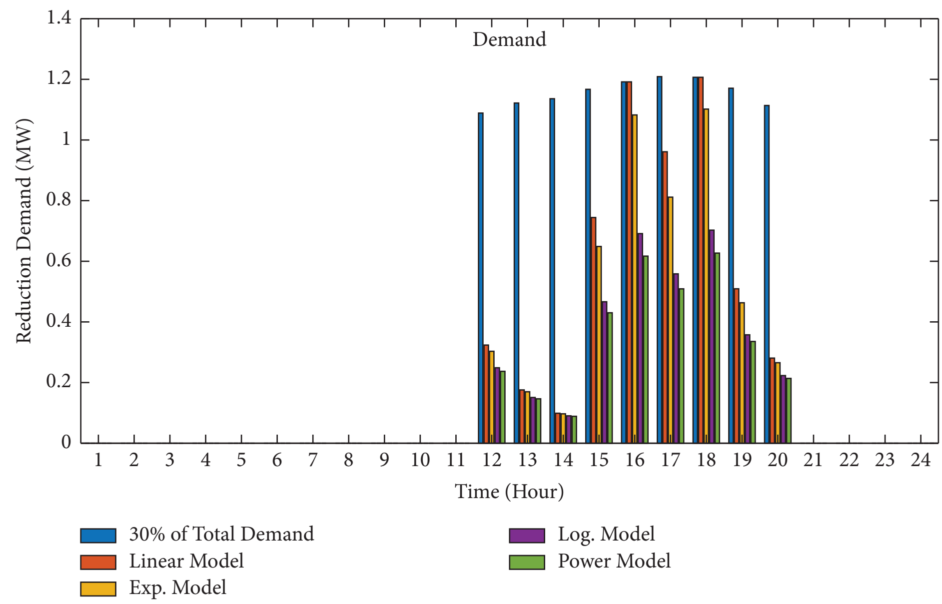

FIGURE 8: Demand reduction in case 3.

TABLE 6: The LSE profit and consumers' cost in case 3.

Model	Maximum percentage of demand reduction (%)	Decreasing the consumers' cost compared to the base case (%)	Consumers' cost ($)	Increasing the LSE profit compared to the base case (%)	The LSE profit ($)
Base case	—	—	5403.74	—	1937.5
Linear	30 at 4 and 6 pm	14.99	4593.98	26.10	2443.14
Exp	27.39 at 4 and 6 pm	13.59	4669.18	23.03	2383.38
Log	17.46 at 6 pm	8.88	4928.26	16.98	2266.57
Power	15.58 at 6 pm	7.88	4977.68	15.78	2243.19

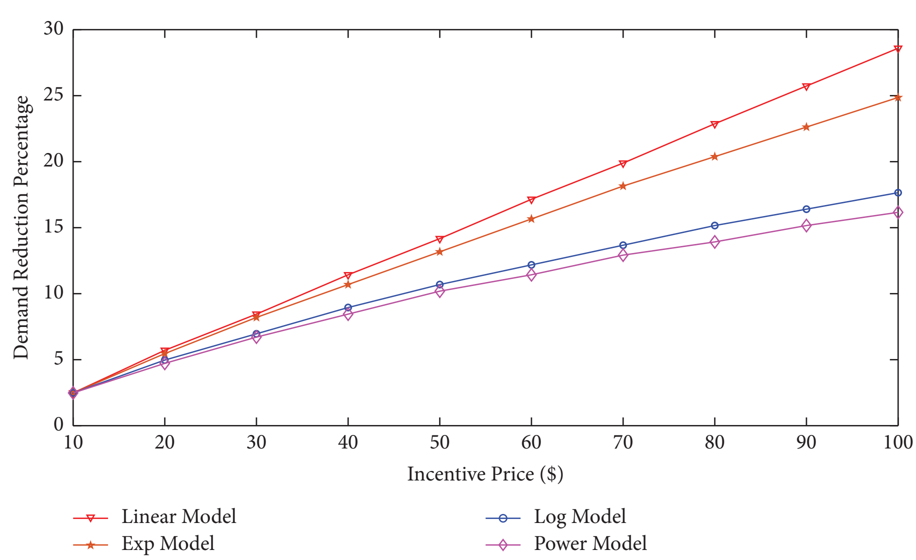

FIGURE 9: The relationship between the incentive price and the load reduction.

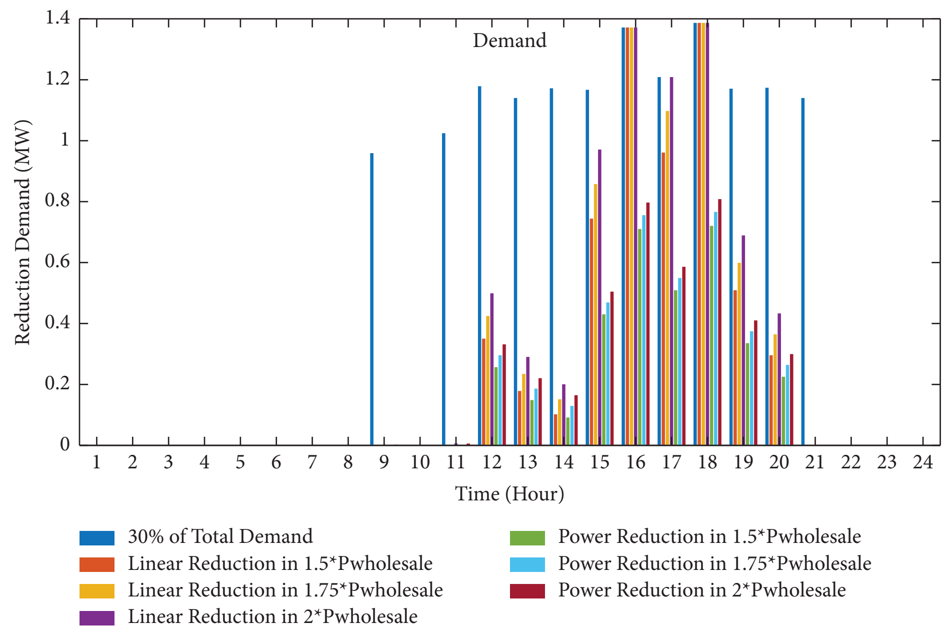

Figure 10: Load reduction changes in the linear and power model due to the P_{dso} changes.

4.4. Case 4: The Proper Incentive Price Paid by the System Operator (P_{dso}) for Implementation. The analysis focuses on determining the optimal P_{dso} and its impact on demand reduction. Different values of P_{dso} were considered, including 1.5 times, 1.75 times, and 2.0 times the wholesale price. The findings show that increasing P_{dso} leads to a greater reduction in demand. However, it is important to strike a balance as excessively high incentive prices may result in unnecessary demand reduction. Based on the analysis, an appropriate incentivizing price of 1.75 times the wholesale price is suggested for achieving the desired maximum allowable load reduction of 30%. The graph illustrates the load reduction resulting from different values of P_{dso} in both linear and power models, comparing them to the 30% threshold in relation to the initial demand.

During off-peak hours, such as 9 AM, 11 AM, and 9 PM, both the linear and power models experienced a decrease in demand when the P_{dso} was increased by 2.0 times. However, this reduction may not always be necessary and may result in reduced demand that is not needed. Considering this, the appropriate incentivizing price may be 1.75 times the wholesale price, as it reduces the demand more appropriately than the other two prices.

In summary, Figure 10 shows how different values of P_{dso} affect demand reduction and provides insights into the optimal incentive price for achieving a maximum allowable load reduction of 30%.

5. Conclusions

In conclusion, this paper provides a comprehensive analysis of incentive-based demand response programs in power grid management, comparing the results obtained from linear and nonlinear models. The study utilizes real data from the hottest day of the year and considers both linear and nonlinear models to determine optimal incentives and load reductions. The findings demonstrate that providing incentives to consumers during peak hours is a more effective approach compared to alternative strategies such as implementing blackouts and paying outage costs. In the first case, where no incentives were offered, the maximum load reduction resulted in a decrease of approximately 6% in the power model's load. However, in the second case, where incentives were provided, it became evident that incentivizing consumers during peak hours aligns with the interests of both the LSE and consumers. Furthermore, the nonlinear model employed in this study yielded additional insights compared to the linear model, highlighting its value in understanding and optimizing demand response programs. The results indicate that both P_{dso} and the maximum load reduction have positive effects on consumers' load reductions and incremental increases in the incentives provided (P_{inc}). Beyond the financial benefits of increased company profits and reduced consumer billing costs, the proposed method also addresses the issue of consumption during peak hours and price spikes. By encouraging load reduction during these periods, the proposed approach contributes to a more sustainable and efficient energy system. Overall, this research enhances our understanding of demand response programs in power grid management and provides valuable insights for system operators and policymakers. By considering the effectiveness of incentives and comparing the results between linear and nonlinear models, this study offers practical guidance for implementing successful demand response initiatives that benefit both energy providers and consumers alike.

Nomenclature

$S(D(t), w)$: Consumer's benefit function ($)

$U(D(t), w)$: Consumer's utility function (\$)
W: Consumer's willingness to their consumption
$D_0(t)$: Initial demand (MWh)
D_s: Supply generated by power plants (MWh)
$D(t)$: Demand after implementing IBDR (MWh)
$\Delta D_{\max}$: Maximum load reduction after IBDRP implementation (MWh)
$\Delta D(t)$: Load reduction after IBDRP implementation (MWh)
$E(t)$: Price elasticity of demand
$P_0(t)$: Retail price before IBDRP implementation (\$/MWh)
$P(t)$: Retail price after IBDRP implementation (\$/MWh)
$P_{\text{inc}}(t)$: Incentive price (\$/MWh)
$P_{\text{retail}}(t)$: Retail price (\$/MWh)
$P_{\text{dso}}(t)$: Incentive price paid by the system operator
$P_{\text{wholesale}}(t)$: Locational marginal price (\$/MWh)
Outage cost: Payment due to power outages.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest, financial or otherwise.

Authors' Contributions

Each author has substantially contributed in conducting the underlying research and drafting this manuscript.

References

[1] B. Astarios, A. Kaakeh, M. Lombardi, and J. Scalise, *The Future of Electricity: New Technologies Transforming the Grid Edge*, World Economic Forum, Cologny, Switzerland, 2017.
[2] I. Pérez-Arriaga and C. Knittle, *Utility of the future: An mit energy iniative response to an industry in transition*, MIT Energy Initiative, Cambridge, MA, USA, 2016.
[3] H. M. Hussain, *Heuristic-Based Packetized Energy Management for Residential Electricity Demand*, Lappeenranta-Lahti University of Technology LUT, Lappeenranta, Finland, 2023.
[4] M. H. Imani, M. J. Ghadi, S. Ghavidel, and L. Li, "Demand response modeling in microgrid operation: a review and application for incentive-based and time-based programs," *Renewable and Sustainable Energy Reviews*, vol. 94, pp. 486–499, 2018.
[5] M. Ghaedi, N. Eslaminia, H. Delkhosh, and M. P. Moghaddam, "A defensive approach against pricing false data injection attacks based on incentive-based demand response and network reconfiguration," in *Proceedings of the 2022 12th Smart Grid Conference (SGC)*, pp. 1–6, Kerman, Iran, December 2022.
[6] T. Dayaratne, C. Rudolph, A. Liebman, and M. Salehi, "Robust demand response for device scheduling under false data injection attacks in smart grids," in *Proceedings of the 2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, pp. 294–298, The Hague, Netherlands, October 2020.
[7] M. Alipour, K. Zare, H. Seyedi, and M. Jalali, "Real-time price-based demand response model for combined heat and power systems," *Energy*, vol. 168, pp. 1119–1127, 2019.
[8] S. Nojavan and K. Zare, *Demand Response Application in Smart Grid*, Springer, Berlin, Germany, 2020.
[9] M. K. Kiptoo, O. B. Adewuyi, H. O. R. Howlader, A. Nakadomari, and T. Senjyu, "Optimal capacity and operational planning for renewable energy-based microgrid considering different demand-side management strategies," *Energies*, vol. 16, no. 10, p. 4147, 2023.
[10] T. Kırant Mitić and K. Voss, "Development of a joint penalty signal for building energy flexibility in operation with power grids: analysis and case study," *Buildings*, vol. 13, no. 5, p. 1338, 2023.
[11] Y. Chai, Y. Xiang, J. Liu, C. Gu, W. Zhang, and W. Xu, "Incentive-based demand response model for maximizing benefits of electricity retailers," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 6, pp. 1644–1650, 2019.
[12] A. D. Papalexopoulos, "Mass market demand response management for the smart grid," *Power Grid Operation in a Market Environment*, vol. 69, 2017.
[13] M. Hussain, Y. Gao, S. Semba, M. Irshad, and F. Shair, "Examination of optimum benefits of customer and LSE by incentive and dynamic price-based demand response," *Energy Sources, Part B: Economics, Planning and Policy*, vol. 15, no. 6, pp. 383–401, 2020.
[14] R. Lu and S. H. Hong, "Incentive-based demand response for smart grid with reinforcement learning and deep neural network," *Applied Energy*, vol. 236, pp. 937–949, 2019.
[15] Q. Shi, C.-F. Chen, A. Mammoli, and F. Li, "Estimating the profile of incentive-based demand response (IBDR) by integrating technical models and social-behavioral factors," *IEEE Transactions on Smart Grid*, vol. 11, no. 1, pp. 171–183, 2020.
[16] A. Asadinejad and K. Tomsovic, "Optimal use of incentive and price based demand response to reduce costs and price volatility," *Electric Power Systems Research*, vol. 144, pp. 215–223, 2017.
[17] X. Fang, Q. Hu, F. Li, B. Wang, and Y. Li, "Coupon-based demand response considering wind power uncertainty: a strategic bidding model for load serving entities," *IEEE Transactions on Power Systems*, vol. 31, no. 2, pp. 1025–1037, 2016.
[18] J. Ponoćko and J. V. Milanović, "Application of data analytics for advanced demand profiling of residential load using smart meter data," in *Proceeding of the 2017 IEEE Manchester PowerTech*, pp. 1–6, Manchester, UK, June 2017.
[19] M. Shakeri, "An autonomous home energy management system using dynamic priority strategy in conventional homes," *Energies*, vol. 13, no. 13, p. 3312, 2020.
[20] M. Yu and S. H. Hong, "Incentive-based demand response considering hierarchical electricity market: a Stackelberg game approach," *Applied Energy*, vol. 203, pp. 267–279, 2017.
[21] P. Harsh and D. Das, "Energy management in microgrid using incentive-based demand response and reconfigured network considering uncertainties in renewable energy sources," *Sustainable Energy Technologies and Assessments*, vol. 46, Article ID 101225, 2021.
[22] M. Yu, S. H. Hong, and J. B. Kim, "Incentive-based demand response approach for aggregated demand side participation," in *Proceedings of the 2016 IEEE International Conference on*

Smart Grid Communications (SmartGridComm), pp. 51–56, Sydney, Australia, November 2016.

[23] A. Asadinejad, K. Tomsovic, and M. G. Varzaneh, "Examination of incentive based demand response in western connection reduced model," in *Proceedings of the 2015 North American Power Symposium (NAPS)*, pp. 1–6, Charlotte, CA, USA, October 2015.

[24] X. Wang, Y. Liu, J. Liu, Y. Jia, and Y. Xiang, "Thermally controllable demand response with multiple load aggregators," *Electric Power Systems Research*, vol. 179, Article ID 106102, 2020.

[25] F. Salah, R. Henriquez, G. Wenzel, D. E. Olivares, M. Negrete-Pincetic, and C. Weinhardt, "Portfolio design of a demand response aggregator with satisficing consumers," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 2475–2484, 2019.

[26] D. Muthirayan, E. Baeyens, P. Chakraborty, K. Poolla, and P. P. Khargonekar, "A minimal incentive-based demand response program with self reported baseline mechanism," *IEEE Transactions on Smart Grid*, vol. 11, no. 3, pp. 2195–2207, 2020.

[27] C. L. Dewangan, "An improved decentralized scheme for incentive-based demand response from residential customers," *Energy*, vol. 284, Article ID 128568, 2023.

[28] L. Malehmirchegini and H. Farzaneh, "Incentive-based demand response modeling in a day-ahead wholesale electricity market in Japan, considering the impact of customer satisfaction on social welfare and profitability," *Sustainable Energy, Grids and Networks*, vol. 34, Article ID 101044, 2023.

[29] X. Fu, Q. He, and Y. Ge, "Strategic bidding model for load service entities considering priced-based and incentive-based demand response," in *Proceedings of the 2023 5th Asia Energy and Electrical Engineering Symposium (AEEES)*, pp. 1377–1382, Chengdu, China, March 2023.

[30] S. S. Gul and D. Suchitra, "A two level model of energy market considering incentive based demand response," in *Proceedings of the 2023 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI)*, pp. 1–6, Chennai, India, April 2023.

[31] M. J. Rana, K. H. Rahi, T. Ray, and R. Sarker, "An efficient optimization approach for flexibility provisioning in community microgrids with an incentive-based demand response scheme," *Sustainable Cities and Society*, vol. 74, Article ID 103218, 2021.

[32] M. A. Fotouhi Ghazvini, J. Soares, N. Horta, R. Neves, R. Castro, and Z. Vale, "A multi-objective model for scheduling of short-term incentive-based demand response programs offered by electricity retailers," *Applied Energy*, vol. 151, pp. 102–118, 2015.

[33] D. H. Vu, K. M. Muttaqi, A. P. Agalgaonkar, and A. Bouzerdoum, "Customer reward-based demand response program to improve demand elasticity and minimise financial risk during price spikes," *IET Generation, Transmission and Distribution*, vol. 12, no. 15, pp. 3764–3771, 2018.

[34] N. Eslaminia and H. Rajabi Mashhadi, "Incentive-based demand response economic model for peak shaving considering load serving entity profit maximization," in *Proceedings of the 2022 30th International Conference on Electrical Engineering (ICEE)*, pp. 144–149, Juje, Korea, July 2022.

[35] P. Samadi, H. Mohsenian-Rad, R. Schober, and V. W. S. Wong, "Advanced demand side management for the future smart grid using mechanism design," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1170–1180, 2012.

[36] P. Siano, "Demand response and smart grids—a survey," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461–478, 2014.

[37] H. A. Aalami, H. Pashaei-Didani, and S. Nojavan, "Deriving nonlinear models for incentive-based demand response programs," *International Journal of Electrical Power and Energy Systems*, vol. 106, pp. 223–231, 2019.

[38] A. Niromandfam, A. S. Yazdankhah, and R. Kazemzadeh, "Modeling demand response based on utility function considering wind profit maximization in the day-ahead market," *Journal of Cleaner Production*, vol. 251, Article ID 119317, 2020.

[39] A. Abdollahi, M. Parsa Moghaddam, M. Rashidinejad, and M. K. Sheikh-El-Eslami, "Investigation of economic and environmental-driven demand response measures incorporating UC," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 12–25, 2012.

[40] Pjm, "Data miner 2- hourly load: metered," 2021, https://dataminer2.pjm.com/feed/hrl_load_metered.

[41] Pjm, "Data miner 2," 2021, https://dataminer2.pjm.com/feed/rt_hrl_lmps/definition.

[42] Electric Rate, "Electricrate – compare electric companies and find the lowest rate," 2021, https://www.electricrate.com/ratefinder/pub/index.php?action=Search%3ARate&ratefinder_custtype=Residential&ratefinder_zipcode=19930.