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Analysis of the Impact of Electricity Price Variations on Self-Healing Improvement in Smart Distribution Networks Considering Consumer Behavior

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ABSTRACT

Self-healing is a capability of smart electricity distribution networks that enables the automatic restoration of the network in the event of a persistent fault. To restore the power supply to loads downstream of the fault location, adjacent feeders can be utilized. However, the use of backup feeders is subject to network technical constraints such as bus voltage levels and permissible line currents. One method to prevent the violation of network constraints during load restoration via backup feeders is the implementation of demand response programs. This paper examines the impact of Critical Peak Pricing (CPP), a price-based program, on the self-healing of smart distribution networks. Two models, exponential and linear, have been considered for modeling the CPP program. Additionally, the impact of different price surges on self-healing improvement has been analyzed. To make the results more realistic, various consumer participation rates in demand response programs have been taken into account. The proposed model has been evaluated using bus number 4 of the Roy-Billinton test system.

1. INTRODUCTION

With the increasing complexity of smart distribution networks, there is a need for detailed studies on topics such as fault detection, fault isolation, and automatic recovery under various fault conditions in the power grid. One of the main requirements of the electricity distribution network is to minimize the impact of natural and unnatural faults with minimal human intervention [1]. Self-healing is a feature of smart distribution networks that enables the network to automatically restore service to isolated loads affected by persistent faults without human intervention [2]. The self-healing process begins by identifying the fault area. Subsequently, the faulted area is isolated from the rest of the network using remotely controllable switches. The next step involves restoring service to loads that are out of service but isolated from the fault as quickly as possible, without violating technical network constraints.

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Various studies have examined self-healing, some of which are discussed below. In reference [3], the impact of redundancy expansion on enhancing the self-healing capability of smart networks was examined using reliability modeling of control and protection systems. This study also separately analyzed the effect of redundancy expansion on each system. The article considered three layers for self-healing: 1- equipment layer, 2- system layer, 3- actions for repairing existing equipment. Reference [4] proposed a linear programming method for locating and selecting types of control switches. This linear programming was evaluated using three scenarios to select the best switch types and configurations. Reference [5] designed a fast restoration method for large-scale distribution systems considering high-priority customers. This study focused on restoring the maximum load with minimal switching operations. Reference [6] implemented a two-stage strategy for network restoration. Initially, a set of practical restoration schemes was generated and then evaluated based on four fuzzy criteria: probable readiness, number of switching operations, number, and amount of load transfer, considering their relative weights, selecting the strategy with the highest index.

Reference [7] presented a multi-agent self-healing approach in the presence of distributed generation for distribution networks. The advantages of this approach include reducing feeder congestion, preventing voltage limit violations, and coordinating reactive power control devices. Reference [8] proposed a new three-state approach using particle swarm optimization to determine the optimal number and location of two types of switches (sectionalizing and circuit breakers) in radial distribution systems. The objective was to minimize customer interruption costs and investment costs. Reference [9] proposed an optimal switch placement method aiming to optimize reconfiguration and service restoration in distribution networks. Reference [10] considered a multi-objective problem for load restoration, with goals including maximizing total restored load, minimizing switching operations, maximizing high-priority restored load, and minimizing load shedding. The author used two methods to solve this problem: one based on analysis and the other a heuristic method based on graphs. Reference [11] improved service restoration using direct load control and load shedding when necessary. The author considered four objectives: prioritizing high-priority restoration, maximizing total restored load, minimizing switching operations, and minimizing load shedding. Reference [12] optimized the placement of control and protective devices using an emergency demand response program. The goal was to minimize interruption costs, investment costs, and maintenance costs of equipment, assuming a constant network load during the restoration process. Reference [13] considered emergency demand response to enhance restoration. Using the particle swarm optimization algorithm, this study reduced the number of restoration strategies and the incentives for responsive loads.

This review indicates a growing focus on enhancing the reliability and resilience of smart distribution networks through various strategies and technological advancements. By examining the impact of different methods and models on self-healing capabilities, researchers can better understand how to design and implement more efficient and effective distribution systems.

As mentioned, one segment of the self-healing process is fault isolation, which, after a fault occurs in the network, uses remotely controllable switches to limit the fault's impact to a section of the network. Once the fault is isolated, the network is divided into three parts: upstream of the fault, the fault area, and downstream of the fault. Loads in the upstream section are restored via the main feeder, but various methods exist for restoring loads located downstream of the fault. In this study, to restore the loads situated downstream of the fault, a backup feeder connected to the main feeder via sectionalizing switches is used. One issue with using the backup feeder is the violation of technical network constraints, such as bus voltage limits and permissible line currents. This paper aims to use the Critical Peak Pricing (CPP) program, a price-based demand response (DR) program, to restore the maximum number of customers without violating technical network constraints. Since the success of DR programs directly depends on consumer participation rates, this paper also considers the participation rate. Considering that network repairs occur over several hours, during which the load demand may increase, this study also accounts for increased consumer loads during the restoration period.

The paper is organized as follows: Section 2 discusses demand response and various DR programs. Section 3 models the objective function and CPP program both linearly and exponentially. Section 4 outlines the technical constraints of the distribution network, such as line current limits. Section 5 describes the features and specifications of the network used for simulation. Section 6 presents the simulation results, and Section 7 provides the conclusion and summary.

2. DEMAND RESPONSE PROGRAMS

Demand response (DR) is a key component of demand-side management, aimed at improving the electricity consumption patterns of industrial, commercial, and residential customers [14]. DR programs are precisely defined as "changes in electricity usage by end-users from their normal consumption patterns in response to changes in the price of electricity over time or to incentive payments designed to induce lower electricity use during times of high wholesale market prices or when system reliability is jeopardized" [15]. Therefore, the overarching goal of DR programs is to enhance network reliability and reduce electricity prices.

DR programs generally fall into two main categories: incentive-based programs and time-based programs [16]. Each category is further divided into various programs based on how incentives are paid and how pricing is structured.

2.1. Time-Based Programs

This category includes several programs such as Real-Time Pricing (RTP), Critical Peak Pricing (CPP), and Time-of-Use (TOU) tariffs. These programs offer customers different rates that reflect the value and cost of electricity at various times. If there is a significant difference between the prices at different hours or periods, customers will shift their usage of flexible loads to times when electricity is cheaper [15].

2.2. Incentive-Based Programs

Incentive-based DR includes programs like Direct Load Control (DLC), Interruptible/Curtailable Load (I/C), Demand Bidding Programs (DBP), Emergency Demand Response Programs (EDRP), Capacity Market Programs (CMP), and Ancillary Services Market Programs (ASMP). These programs offer incentives for voluntary load reduction by consumers during critical periods.

3. MODELING AND CONSTRAINTS OF THE PROBLEM

The Critical Peak Pricing (CPP) program incentivizes consumers to shift their electricity usage patterns during specific hours of the year by significantly increasing electricity prices to several times the base price. As a result, consumers defer non-essential tasks to other hours of the day, reducing electricity consumption. The price hike associated with the CPP program occurs during high-demand periods of the year or when a fault occurs in the network.

The objective function of the problem is shown in equation (1). Since implementing the CPP program does not impose any cost on distribution companies, only the interruption cost to consumers is included in the objective function. Equation (2) specifies how to calculate the total consumer interruption cost.

$$Min\ Fit = TCIC \tag{1}$$

$$TCIC = \sum_{t} \sum_{i \epsilon LP} \sum_{j \epsilon EC} \sum_{z \epsilon KLP} P_{ijt} \varphi_{iz} \theta_z \lambda_j LPS_{ijt} \tag{2}$$

In this paper, the CPP program is modeled in two ways. The first model is linear, as shown in equation (3) [17]. Since linear modeling is easier to implement, it is preferable when price increases are not substantial because at lower prices, the results of different modeling approaches do not differ significantly. However, when price increases are substantial during critical times, linear modeling is less effective as it fails to accurately capture consumer behavior in response to high price increases, as discussed in section 6. Therefore, in this paper, the CPP program is also modeled exponentially, as represented by equation (4) [18].

$$d_{izt} = d_{izt}^0 * (1 + \frac{E_z[\rho_{iz} - \rho_{iz}^0]}{\rho_{iz}^0}) \quad (3)$$

$$d_{izt} = d_{izt}^0 * EXP(\frac{E_z[\rho_{iz} - \rho_{iz}^0]}{\rho_{iz}^0}) \quad (4)$$

To examine the impact of consumer participation rates in the CPP program, equations (5) and (6) are used.

$$d_{izt} = d_{izt}^0 * (1 + \frac{E_z[\pi * \rho_{iz} - \rho_{iz}^0]}{\rho_{iz}^0}) \quad (5)$$

$$d_{izt} = d_{izt}^0 * EXP(\frac{E_z[\pi * \rho_{iz} - \rho_{iz}^0]}{\rho_{iz}^0}) \quad (6)$$

In the formulas above, elasticity refers to the following definition:

"Elasticity of demand refers to the sensitivity of load to price changes [13]."

In this paper, the elasticity of various types of loads is considered according to Table 1. It should be noted that the higher the absolute value of elasticity, the more sensitive the load is to price changes. This means that if the electricity price increases, the load with higher elasticity will reduce its power consumption more significantly. A value of zero indicates that the load is completely inelastic, meaning that even with an increase in electricity price or incentive payments, it does not reduce its power consumption. The elasticity of residential loads is considered based on the study in [17]. For commercial loads, given that power outages affect their sales, they are less inclined to reduce consumption in response to price increases, and their elasticity is considered to be 0.05 in this paper. For industrial loads, which often have emergency power sources and can switch to these sources if electricity prices rise, elasticity is assumed to be higher than that of commercial loads. Public and critical loads are considered completely inelastic [19].

Table 1. Elasticity of various subscriber types [19]

Subscriber Type	**Residential**	**Commercial**	**Industrial**	**Public**	**Sensitive**
Elasticity	-0.15	-0.05	-0.10	0	0

4. OTHER CONSTRAINTS OF THE PROBLEM

To find the optimal strategy, initially, strategies that cannot satisfy the problem's constraints must be excluded. This is achieved by performing load flow analysis in the network. Additionally, the load flow analysis helps determine the extent of load response participation that can satisfy the technical constraints of the problem. The technical constraints of the problem are defined as follows [20]:

- Radial Structure of the Network: Throughout and after the recovery process, the radial structure of the network must be maintained, and under no circumstances should a loop be formed in the network.

- Bus Voltage Magnitudes: The longer a feeder, the greater the voltage drop in that feeder. Load points must be supplied within an acceptable voltage range. This constraint is specified by Equation (7).

$$V^{min} \leq |V_{ijt}| \leq V^{max} \qquad \forall i \epsilon LP, j \epsilon EC, t \epsilon FT \tag{7}$$

- Permissible Line Currents: This constraint is the thermal constraint of the lines, which is the most critical constraint during the recovery process. Each feeder can supply a specific amount of load. Therefore, when transferring recoverable loads to adjacent feeders, the distribution company must, after solving the load flow problem, verify whether it is feasible to transfer all load points to the given adjacent feeder. This constraint is represented in Equation (8).

$$I_{ij} \leq I_{br}^{max} \qquad \forall i \epsilon BR, j \epsilon EC, t \epsilon FT \tag{8}$$

5. THE STUDIED NETWORK

To evaluate the proposed methods for improving self-healing in distribution networks, bus number 4 of the Roy-Billinton test system is used. As shown in Figure 1, this network has three sub-transmission substations with a voltage of 33 kV, seven 11 kV feeders, 38 load points at 415 volts, and 4779 consumers. This network is equipped with remotely controllable switches with a zero failure rate, and the operation time of these devices is considered to be 30 seconds. The average load of this network is 24.58 MW, and its peak load is 40 MW. It is assumed in this paper that the load increases during the network recovery hours [20].

Additionally, in the sample network, the resistance and reactance of the lines are 0.307 and 0.6295 ohms per mile, respectively. The maximum permissible current through the lines, as mentioned in the previous section, is 530 amperes, and the minimum and maximum permissible bus voltages are considered to be 0.95 and 1.05 per unit, respectively [13]. The failure rate of the lines is considered to be 0.065 faults per kilometer per year, and the failure rates of load buses and transformers are 0.001 and 0.015 faults per year, respectively. The repair time for lines after a fault in the network is assumed to be two hours. The repair time for a load bus fault is considered to be three hours. Moreover, since a significant amount of time (approximately 50 to 200 hours) is required for transformer repairs, it is assumed here that in the event of a transformer failure, it is replaced with a reserve transformer, a process that takes five hours [19].

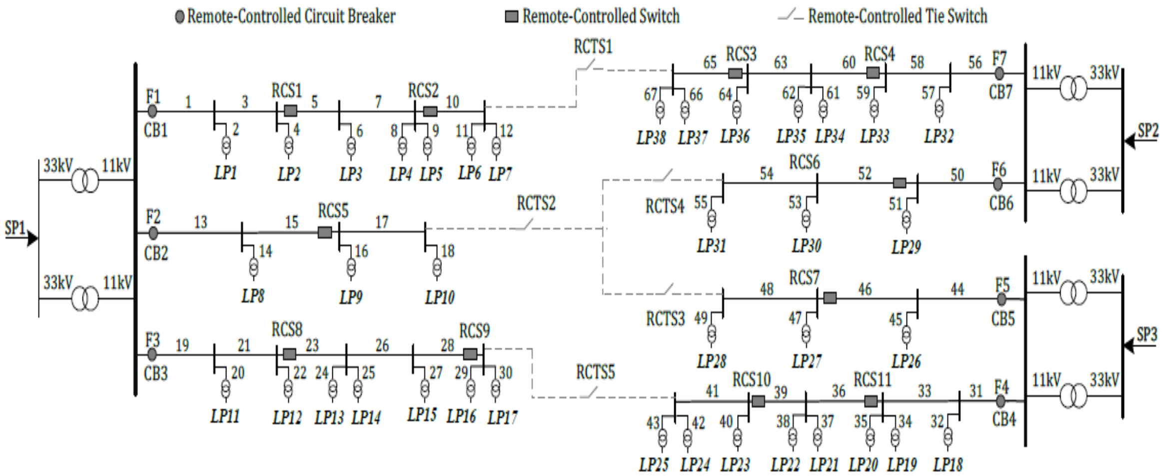

Fig.1. Overview of the studied system (RBTS-4)

The loads in this network are categorized into five groups according to [20]: residential, commercial, industrial, public, and critical. Critical loads are subscribers for whom any interruption in service can be considered a significant issue. Such interruptions can lead to irreparable consequences, both financially and in terms of human life, for these subscribers. Examples of these consumers include hospitals, police stations, fire stations, and others. While interruptions in service to public subscribers do not cause as much damage as those to critical loads, they still cause public concern and disrupt the process of providing services to the populace. Examples of public loads include schools and educational institutions, non-critical government offices, and others. Table 2 presents the penalties that the distribution company must pay in the event of a power outage for each type of subscriber. As observed, the highest penalty is associated with critical loads, as previously mentioned, because service interruptions for these loads result in significant damages [19].

Table 2. Penalty for failing to supply electricity to consumers [20]

Subscriber Type	Residential	Commercial	Industrial	Public	Sensitive
Penalty ($\frac{\$}{KWh}$)	0.695	10	9.64	38.3	63.8

6. SIMULATION RESULTS

For the simulation, it is assumed that the price of electricity during a fault occurrence increases fourfold from the base price, both in linear and exponential scenarios. Based on this assumption, the results of the simulation under various consumer participation rates were obtained, which are detailed below.

Table 3 examines the costs associated with consumer outages and certain reliability indices for different scenarios, including the base case (where the existing network is considered without any demand response programs), linear modeling with 100% consumer participation, and exponential modeling with 100% consumer participation. The cost due to outages in the base case is approximately $171,000. By employing the critical peak pricing program, this cost is reduced to $88,000 in the linear scenario and $95,000 in the exponential scenario. This reduction in payments by distribution companies translates to higher profits and increased satisfaction for these companies using the critical peak pricing program. Additionally, the SAIDI index, which represents the average interruption duration per system, is 0.6825 in the base case without the critical peak pricing program. This index decreases to 0.4774 in the linear scenario and 0.4763 in the exponential scenario when the critical peak pricing program is applied. This reduction in system interruption duration means enhanced consumer access to electricity service and consequently increased consumer satisfaction. Regarding the SAIFI index, which indicates the frequency of system interruptions, the values in both the base case and under the critical peak pricing program remain identical at 0.5742. The lack of improvement in this index is because it depends on the number of consumer outages per year and the total number of consumers, parameters that cannot be improved through demand response programs.

Table 3. Results of implementing the critical peak pricing program

Status	Cost($\frac{\$}{yr}$)	SAIFI	SAIDI	CAIDI
Base	170795.855	0.5742	0.6825	1.1885
Linear Model of Critical Peak Pricing	88462.550	0.5742	0.4774	0.8313
Exponential Model of Critical Peak Pricing	94683.442	0.5742	0.4783	0.8294

Figures 2 and 3 respectively illustrate the annual outage duration of load points and the total interruption cost for all consumers across these load points, given full participation in the critical peak pricing program. As observed in these figures, the total interruption cost and outage duration have decreased in some load points with the critical peak pricing program, while in other load points, there has been no change.

For example, the interruption cost and duration for load points 1 and 2 have not changed. This is because, in the event of a fault in any of the equipment between the remotely controlled circuit breaker RCCB1 and the remotely controlled switch RCS1, it is impossible to isolate these two load points from the fault. Therefore, these two load points cannot be restored during such faults, even with the presence of the critical peak pricing program, rendering the demand response program ineffective in reducing the outage duration for these points. Additionally, in the case of a fault in all equipment between RCS1 and RCTS1, load points 1 and 2 can be restored without the demand response program. Thus, the demand response program does not affect load points 1 and 2.

Another example is load points 32 and 33, where the interruption cost and duration also remain unchanged. This is because, in the event of a fault in any of the equipment between RCCB7 and RCS4, these load points cannot be restored. Moreover, in the event of a fault in all equipment between RCTS1 and RCS4 during all restoration hours without the critical peak pricing program, load points 32 and 33 can be restored by opening the RCS4 switch and closing the RCCB7 breaker via the main feeder. Therefore, the critical peak pricing demand response program does not impact the interruption cost and duration for load points 32 and 33.

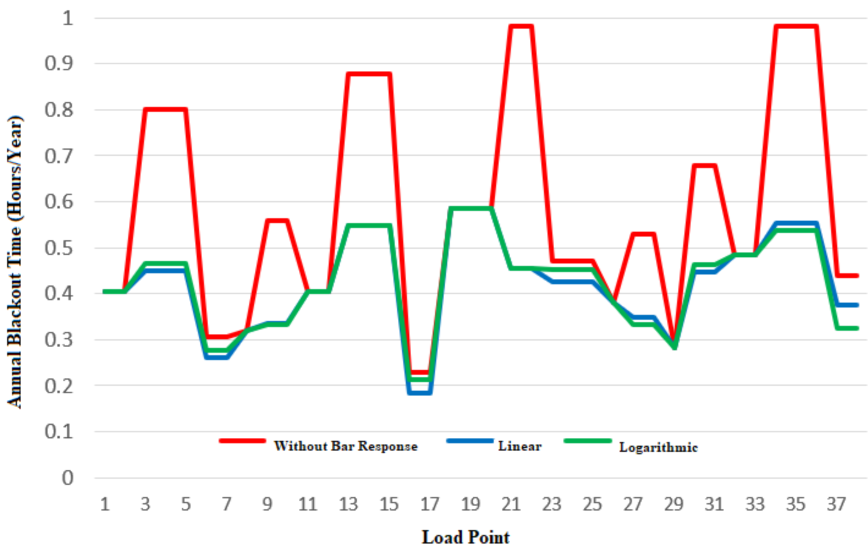

Fig.2. Impact of critical peak pricing program on the annual outage duration of load points

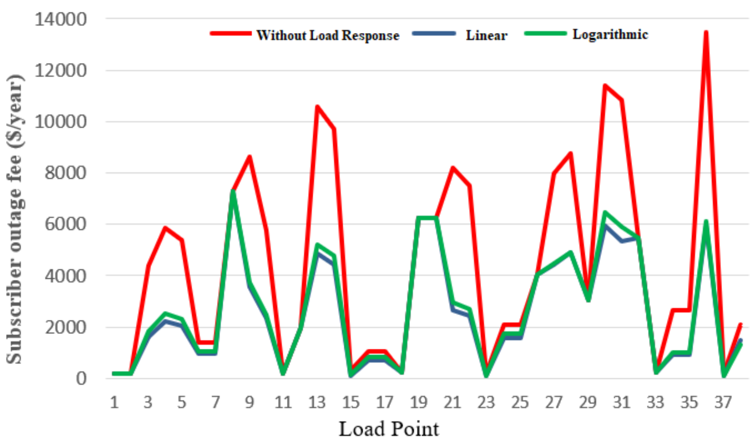

Fig. 3. Impact of critical peak pricing program on the total interruption cost of load points annually

Figures 4 and 5 respectively show the impact of the linear and exponential models of the critical peak pricing program on the electricity consumption of load points, with varying rates of consumer participation. As evident from these figures, the critical peak pricing program significantly reduces electricity consumption by consumers only if more than 50% of consumers participate in the demand response program.

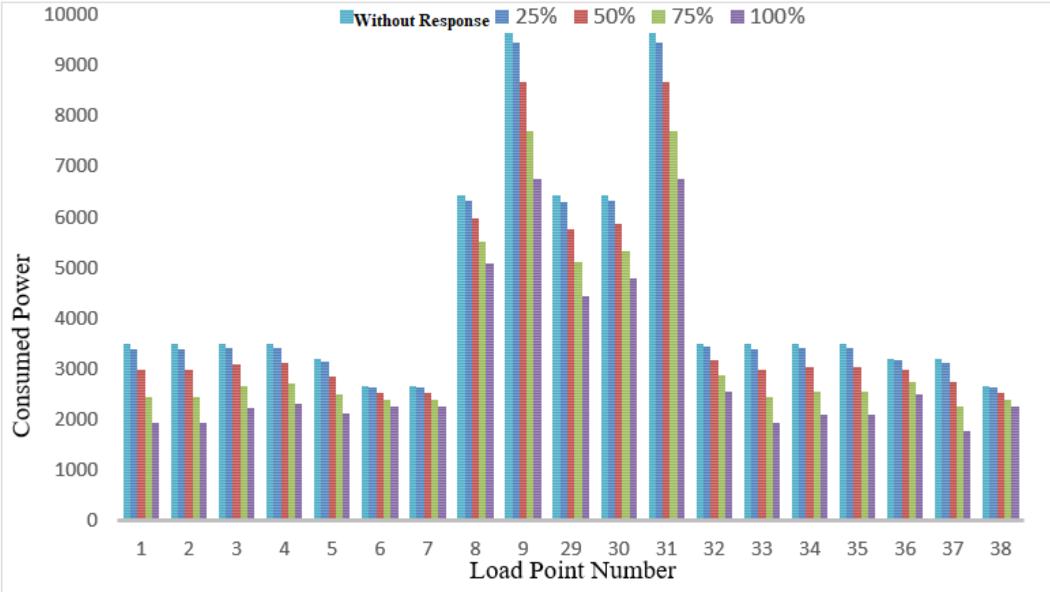

Fig.4. Impact of consumer participation on electricity consumption in the linear model of the critical peak pricing program

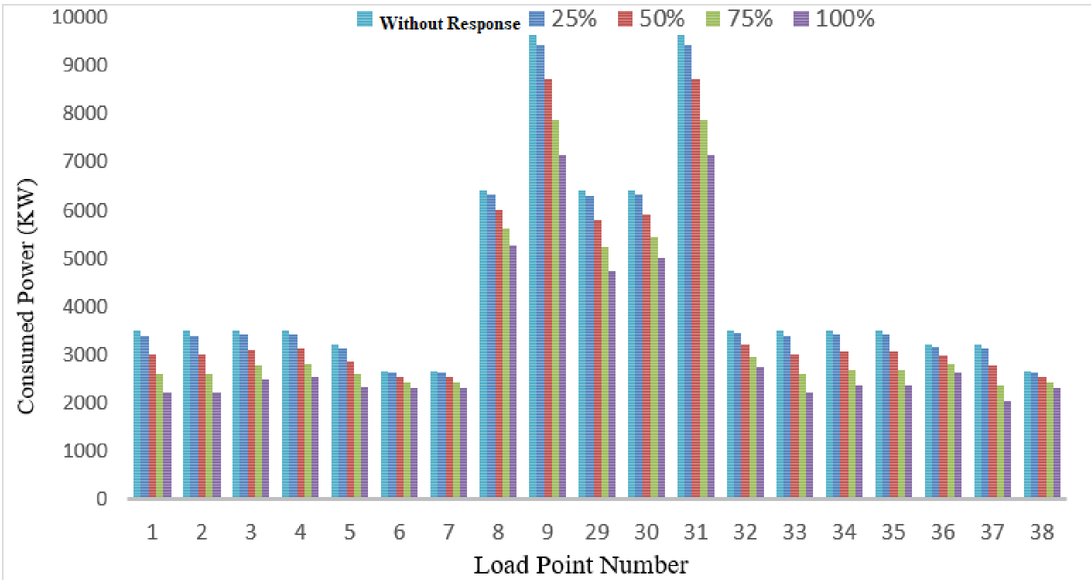

Fig.5. Impact of consumer participation on electricity consumption in the exponential model of the critical peak pricing program.

Figure 6 illustrates the changes in the System Average Interruption Duration Index (SAIDI) and the costs incurred from consumer outages under scenarios without demand response and with the linear model of the critical peak pricing program, considering varying levels of consumer participation. As indicated in the figure, the reduction in outage costs is more pronounced when at least 50% of consumers participate in the critical peak pricing program.

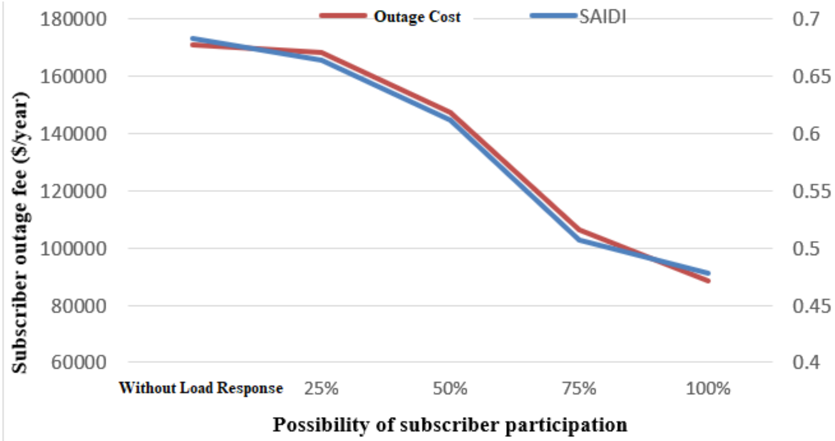

Fig.6. Impact of consumer participation on outage costs and SAIDI in the critical peak pricing program

To examine the impact of price increases on improving self-healing in the distribution network, four scenarios were considered where the electricity price during a fault occurrence increased to six, five, four, and three times the base price, respectively. Table 4 presents the costs incurred from consumer outages and certain reliability indices for these scenarios.

Table 4. Impact of price increases on outage costs and SAIDI

Status / Senario	Linear Model		Logarithmic Model	
	Cost	SAIDI	Cost	SAIDI
Senario 1	60461.503	0.4403	78989.337	0.4642
Senario 2	74284.346	0.4545	90270.613	0.4700
Senario 3	88462.550	0.4774	94683.442	0.4783
Senario 4	109848.602	0.5102	113425.433	0.5218

As previously mentioned, when the price increase is not significant, there is no substantial difference between the linear and exponential models. For instance, in Scenario 4, the outage cost in the linear model is around $109,000, while in the exponential model, it is approximately $113,000. The difference in outage costs between the two models is about $4,000. In contrast, the difference in Scenario 1 is around $18,000.

As shown, the changes in the SAIDI index in the exponential model between Scenarios 1 and 2 are not substantial compared to Scenario 3. This is because, with a fourfold increase in peak price, most removable loads and loads that can be used at other times are already cut off, leaving few removable loads in the network. With further peak price increases, these remaining loads are gradually disconnected until no more removable loads are left, and only essential and sensitive loads remain connected to the network. Hence, beyond a certain point, price increases do not significantly impact reliability indices and only lead to consumer dissatisfaction due to the excessively high electricity prices. In the linear model, electricity consumption continues to decrease with price increases until it theoretically reaches zero, which is unrealistic since some essential loads will always remain connected at any price. As previously stated, the linear model does not accurately represent consumer behavior, which is evident from Table 4.

Figure 7 shows the changes in the SAIDI index and the costs incurred from consumer outages in the exponential model across different scenarios. As illustrated, a fivefold or sixfold increase in peak prices does not significantly alter the SAIDI index. Therefore, to mitigate the pressure of price increases on consumers, it is recommended that during critical periods, electricity prices increase by approximately five times.

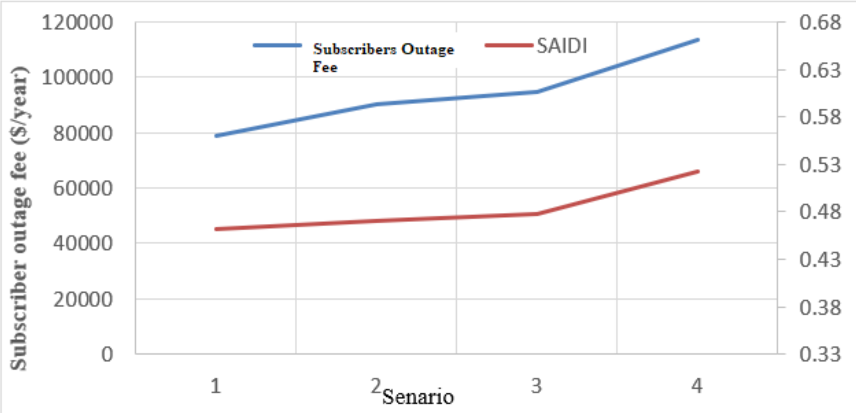

Fig.7. Impact of various scenarios on outage costs and saidi in the exponential model

7. SUMMARY AND CONCLUSION

In recent years, one of the primary demands from consumers to distribution companies has been the provision of uninterrupted electricity. Given the penalties that distribution companies must pay if they fail to supply electricity, these companies are also motivated to ensure no interruptions in the network or to minimize the duration of any interruptions. Consequently, many experts in the electricity industry have focused on adopting economic solutions to improve the reliability of electrical distribution systems. One of the proposed solutions in recent years is smart distribution networks, which facilitate self-healing capabilities.

The objective of this paper is to reduce consumer outage durations while satisfying the network's technical constraints. To achieve this goal, demand response programs were utilized, and simulations were conducted using the critical peak pricing program in both linear and exponential modeling scenarios. The results were presented in the previous sectio

These demand response programs were implemented on bus number 4 of the Roy Billinton test system. This bus includes various types of consumers, such as residential, commercial, industrial, public, and sensitive loads. It was assumed in this study that these loads would exhibit different reactions to electricity price changes and would not reduce their electricity consumption uniformly. For instance, it was assumed that sensitive and public loads would not participate in the demand response program at all.

Based on the simulation results, it is evident that while this program does not prevent faults in the network, it significantly improves reliability indices. This improvement leads to increased consumer satisfaction with the performance of distribution companies and also reduces the costs for these companies.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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