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# Reliability improvement of electrical distribution systems with optimal price, location and amount of participated load in demand response program

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**Abstract:**
In today society, the importance of creating highly reliable distribution networks cannot be overstated. Utilities face challenges in planning and developing these systems effectively, aiming to decrease costs and meet consumer demands. This research proposes a coordinated architecture that focuses on the integration of a Demand Response Program (*DRP*) to improve the reliability of power distribution networks. Specifically, in this paper the reliability improvement is presented through finding the optimal price, location, and amount of participated load in the demand response program considering automatic switches and ESUs in the service restoration process in electrical distribution systems. Also, uncertainty of repair time for faulted equipment is considered in this paper. the suggested objective is to minimize the Total Cost of the system ($TC$) by optimizing the placement of the price, location, and amount of participation loads. The $TC$ includes the cost of customer interruption, energy not supplied, ESU participation, and *DRP*. To illustrate the applicability and efficiency of the suggested approach, it is applied to three cases on a test case. Additionally, a sensitivity study is conducted. The results demonstrate that optimizing the incentive and penalty costs leads to significantly reduced *SAIDI* index and total costs. Moreover, the value of the incentive and penalty costs is lower than the fixed ones in this study, resulting in increased participation of sensitive load points in *DRP*.

**Keywords:** Demand response programReliability; Power distribution system; Energy storage units

## 1. Introduction

The reliability of distribution networks plays a crucial role in ensuring social welfare, particularly in today's energy-dependent society. When deregulated electricity markets have been implemented, electric utility firms are engaged in a competitive atmosphere, striving to identify effective solutions for improving the reliability of their power distribution systems [1].

The reliability level of a power distribution system is determined by its ability to respond effectively to failures. The malfunctioning area is isolated in the case of an outage by locating the problematic component. [2]. The next step is to re-energize the affected load points using a well-executed service restoration plan, with the aim of reducing the average consumer interruption time. One possible approach to enhance the restoration procedure is by utilizing ESUs (Energy Storage Units) to restore power to both the faulty area and downstream areas of the faulty feeder [3]. The capacity of the backup feeding line is increased in terms of required power by putting ESUs in the backup feeding route, including the backup feeder and recoverable loads. By using ESUs, more interrupted loads may be shifted to the auxiliary feeder, lessening the discomfort for consumers in the region that is interrupted [4, 5]. Distribution automation (DA) may considerably decrease frequency and length of power distribution system outages in addition to integrating ESUs into service restoration process. Control switches are crucial to the process of restoring service, making DA methods crucial for enhancing system reliability. As a result, numerous important research studies have been conducted, supplying several practical DA techniques for power distri-

**Table of NOMENCLATURE.**

| | |
|---|---|
| Sets: | |
| $\Omega^{S}$ | Set of scenarios |
| $\Omega^{Py}$ | Set of planning years |
| $\Omega^{Cnt}$ | Set of contingencies |
| $\Omega^{LP}$ | Set of load points |
| $\Omega^{RT}$ | Set of restoration time |
| Constants: | |
| $\pi_s$ | Probability of scenario $s$ |
| $Int$ | Interest rate |
| $\lambda_j$ | Failure rate of equipment $j$ |
| $P_{ik}^{D}$ | The active power demand |
| $\rho_i$ | Price of electricity |
| $t^{AS}$ | automatic switching time |
| $\pi_{ij}^{AS}$ | Probability of correct switching |
| $\eta_{ch,dch}$ | charge and discharge performance rate |
| $\rho_{it}^{inc}$ | Capacity payment to ES in bus $i$ |
| $p_i^{Pr}$ | Probability of customer's responding |
| $q_i^{Pr}$ | Probability of customer's not responding |
| $\beta_{lt}$ | Binary constants equal to 1 if switch is closed |
| $cap_l$ | Maximum Branch capacity |
| $M$ | Big M |
| $N_i$ | Number of customers in load i |
| $SOC_i^{max}$,$SOC_i^{min}$ | the max and min permissible state of charge of the ESU |
| $P_i^{dch,max}$,$P_i^{ch,max}$ | max permitted active power of the ESU |
| $RL_i^{Max}$ | max value of consumers' DRP participation |
| $r_l$ | Resistance |
| $x_l$ | Reactance |
| $\underline{V}$,$\bar{V}$ | Min/Max voltage |
| Functions | |
| $SAIDI$ | System average interruption duration index |
| $TCIC$ | overall cost of customer interruption |
| $TCENS$ | overall cost of energy not supplied |
| $TCES$ | total cost of incorporating ESUs |
| $CDRP$ | cost of executing DRP |
| $TC$ | total cost |
| Variables | |
| $CIC_{ijkts}$ | Customer interruption cost at contingency $j$, load point $i$, scenario $s$, year $k$ |
| $CENS_{ijkts}$ | Cost of unsupplied energy at contingency $j$, load point $i$, year $k$, scenario $s$. |
| $CDF_{ij}\ (rt_{ijkts})$ | Customer damage function |
| $rt_{ijkts}$ | Restoration time for bus $i$, hour $t$, $j^{th}$ contingency, year $k$, scenario $s$ |
| $P_{ijkt}^{es}$ | Delivered active power to $i^{th}$load, $j^{th}$ contingency, time $t$, year $k$ |
| $PTL_{ijkt}\ (DRP,ES)$ | a binary variable that equals to 1 if the load $i$ can be energized by the backup feeder |
| $t_{ijs}^{rep}$ | repair time of contingency $j$ in scenario $s$ |
| $SOC_{ijkt}^{es}$ | ESUs state of charge |
| $CDRP$ | the net cost of DRP |
| $C_{ik}^{Inc}$,$C_{ik}^{Pen}$ | incentive and penalty charges |
| $LC_i^{DRP}$ | Reduced percentage of demand |
| $C_i^{inc}$ | Incentive cost |
| $C_i^{pen}$ | Penalty cost |
| $P_{kt}^{sub}$ | The net active power injected |
| $Q_{kt}^{sub}$ | The net reactive power injected |
| $V_{mt}$ | Voltage level |
| $V_{it}$ | Voltage level |

bution networks [6–8].
Despite the deployment of DA improving power distribution system reliability, Due to backup feeder's capacity limitations, users in regions of malfunctioning feeders that experienced power outages may continue to be without electricity. In such cases, incorporating ESUs and utilizing Demand Response Programs (*DRP*s) in the service restoration process can significantly enhance the efficiency with which DA execution [9]. ESUs and *DRP*s are essential since they increase the capacity of customers' desired energies in backup feeders and locations that aren't getting power in minimizing disruptions and ensuring prompt power restoration during faults. In the event of a fault, until the issue is resolved, all loads in the affected areas are temporarily suspended. Fig. 1 illustrates an example where a failure in line 3 causes the CB1 to open, resulting in a temporary disruption of all load points in F1. Following this, both automatic switch number 1 and 2 (RSC1 and RCS2) as upstream and downstream are opened. The power flow is then examined to determine if the backup feeder (F2) could supply power to restorable loads (LP4-LP5). Load number 3 (LP3) is also located in damaged area in particular case. However, by employing *DRP*, it becomes feasible to supply power to as many loads as possible during breakdowns. *DRP*s are market-based programs that can be considered a hybrid of Direct Load Control (DLC) and Interruptible/Curtailable (I/C) programs.
Numerous research have been done to determine how well load flexibilities work to solve the problem. The capacity for consumers to control their demand and reduce their costs through demand response systems is a key advantage. [10]. From a market perspective, demand response schemes play a crucial role in mitigating price spikes and resolving power market challenges [11]. The system operator can decrease demand during peak times, resulting in the postponement of operating expensive and environmentally harmful units [12]. Studies have examined the potential effects of demand response on residential consumers, which involve modifying load profiles based on flexibility [13]. Demand management contracts, in contrast to switches that are set in certain places, are intended to save electric utility costs while also attracting consumers, according to [14]. It has also been investigated [15] whether demand response tactics are useful in cutting down on customer disruption expenses. Additionally, studies have determined the best periods for responsive loads in households and examined the best times for charging and discharging hybrid electric vehicles based on consumer preferences [16]. Moreover, previous studies have investigated the impact of electrical parking lots, ESUs, and the commitment of *DRP*s on the reliability of power distribution systems [4, 17–19]. This reference presents a coordinated architecture that takes into account the presence of a *DRP* to improve the reliability of a power distribution system. The architecture focuses on strategically placing automated switches and ESUs while considering the uncertainty associated with repair time. By leveraging the capabilities of *DRP*s, automated switches, and ESUs, the architecture aims to optimize the reliability and performance of the power distribution network. [9]. To the best of our knowledge, no work has used the stochastic optimization model for AEDS's maintenance scheduling.
To the best of our knowledge, no work has considered the price, location, and amount of demand response program in reliability study in the distribution system. A demand response program's level of customer engagement directly affects the likelihood of having the extra capacity to supply disrupted demands via a backup feeder, which boosts dependability. Although there have been numerous papers published on reliability enhancement, there is a notable gap in the literature regarding the specific emphasis on the influence of demand response program factors, such as price, location, and amount, within the scope of reliability improvement. This research aims to address this gap and explore the impact of demand response program dynamics on reliability improvement. Thus, in this paper, the reliability improvement is presented by finding the optimal price, location, and amount of participated load in demand response program considering automatic switches and ESUs in service restoration process in electrical distribution systems. Also, uncertainty of repair time for faulted equipment is considered in this paper. This paper introduces a recommended objective function that aims to minimize the total cost of the system ($TC$), which encompasses several cost components such as customer interruption cost, energy not supplied cost, ESU participation cost, and *DRP* cost. The proposed procedure is organized into three distinct cases: Case I explores an electrical distribution system equipped with automatic switches and ESUs but without *DRP*. Case II focuses on an electrical distribution system with automatic switches and ESUs, emphasizing the identification of optimal load participation locations and amounts while considering a fixed price for *DRP*. Case III investigates an electrical distribution system with automatic switches and ESUs, aiming to identify the optimal load participation price, locations and amounts within a *DRP* framework. The paper also includes a sensitivity analysis to further enhance

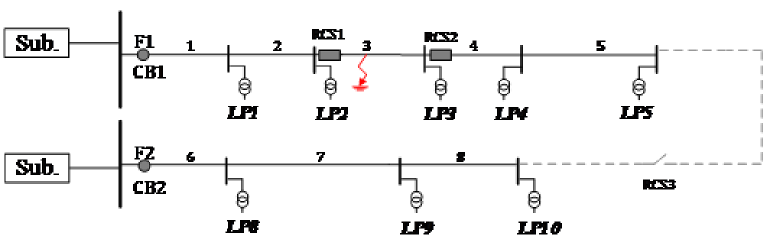


**Figure 1.** Sample distribution system.

understanding. The subsequent sections of the paper delve into problem formulations (Section 2), solution techniques (Section 3), numerical case studies (Section 4), sensitivity analysis (Section 5), and concluding remarks (Section 6).

## 2. Problem formulation

The well-being of society is directly impacted by the reliability of electricity distribution networks, especially for consumers who rely on these systems. To address this, various mathematical procedures and approaches have been developed to enhance power distribution system reliability. This paper proposes a novel approach to improve reliability by optimizing the price, location, and amount of load participation in a demand response program. The approach takes into account the integration of automatic switches and ESUs in service restoration process of electrical distribution systems. In this section, an optimization formulation is introduced, which serves as a fundamental tool in this paper's research methodology for achieving reliability improvement.

### 2.1 Objective function

The purpose of this study's goal is to reduce the total cost of the electrical distribution system. This total cost ($TC$) comprises several elements: the overall cost of customer interruption ($TCIC$), energy not supplied expenditures ($TCENS$), incorporating energy storage units ($TCES$), and cost of executing demand response programs ($CDRP$).

$$TC = TCIC + TCENS + TCES + CDRP \tag{1}$$

By minimizing these cost components, the objective function aims to achieve the desired reduction in the total cost of the system.
Total cost of customer interruption ($TCIC$), which accounts for a sizeable amount of the costs borne by power distribution system companies as a result of outages. This cost component accounts for the financial impact of service interruptions experienced by customers, highlighting its importance in assessing the total cost of outages for utilities.

$$TCIC = \sum_{s\in\Omega^s} \pi_s . \sum_{k\in\Omega^{Py}} \left\{ \begin{array}{l} \left(\dfrac{1}{1+Int}\right)^k .(1+q)^{k-1} \\ . \left[ \sum\limits_{i\in\Omega^{LP}} \sum\limits_{j\in\Omega^{Cnt}} CIC_{ijkts} \right] \end{array} \right\} \tag{2}$$

$$TCENS = \sum_{s\in\Omega^s} \pi_s . \sum_{k\in\Omega^{Py}} \left\{ \begin{array}{l} \left(\dfrac{1}{1+Int}\right)^k .(1+q)^{k-1} \\ . \\ . \left[ \sum\limits_{i\in\Omega^{LP}} \sum\limits_{j\in\Omega^{Cnt}} CENS_{ijkts} \right] \end{array} \right\} \tag{3}$$

Moreover, $\pi_s$ is the Probability of scenario $s$.
To determine the overall interruption cost, equation (2) takes into account all possible contingency situations that may lead to load point outages in the power distribution system. The customer interruption cost ($CIC_{ijkts}$) is calculated for each contingency ($j$) and scenario ($s$), assuming that the load point $i$ cannot be energized in year $k$. Additionally, equation (3) considers the cost of unsupplied energy ($CENS_{ijkts}$) at the contingency ($j$), considering the unavailability of load point $i$ in year $k$ and scenario $s$. It is important to note that equation (2) and equation (3) incorporate the assumption of a constant interest rate ($Int$) and the load growth rate $(1+q)^{k-1}$ during the planning period.
Equations (4) and (5) are utilized to calculate the customer interruption cost ($CIC_{ijkts}$) and the cost of unsupplied energy ($CENS_{ijkts}$) specifically for line and transformer failures. These equations incorporate the restoration time ($rt_{ijkts}$) for load $i$ in year $k$, scenario $s$, and contingency $j$, as determined by equation (6). Equation (6) involves the estimation of the potential of transferring load ($PTL_{ijkt}$ $(DRP, ES)$) through load flow analysis, incorporating ESU and conducting the $DRP$. The binary variable $PTL_{ijkt}$ $(DRP, ES)$ indicates if the backup feeder can activate load $i$ during the repair period at contingency $j$. Additionally, equation (6) considers delivered active power ($P^{es}_{ijkt}$) to load $i$ through the ESUs, the automatic switching time ($t^{AS}$), and the probability of successful switching ($\pi^{AS}_{ij}$) for load $i$ under failure $j$. The switching and load-moving capability, as well as the current power of the integrated ESU, all affect the restoration time. If load i can be moved to the backup feeder, the restoration time will be equal to the switching time ($t^{AS}$). Otherwise, if load $i$ cannot be moved, the installed ESU's installed power will have a direct impact on the restoration time. The repair time of contingency $j$ in scenario $s$ is represented by $rt_{ijkts}$=(1-$P^{es}_{ijkt}/P^{D}_{ik}$).$t^{rep}_{ijs}$. If switching is impossible because the automated control process has failed, such as switch or connection system failures, each hour's restoration time will be based on the installed ESU's current power. Moreover, Customer damage function is shown as $CDF_{ij}(rt_{ijkts})$ and the price

$$CIC_{ijkts} = \lambda_j .(P^D_{ik} - P^{es}_{ik} - LC^{DRP}_i .P^D_{ik}).CDF_i(rt_{ijkts}), \quad \forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, t \in \Omega^{RT}, k \in \Omega^{Py}, s \in \Omega^s. \tag{4}$$

$$CENS_{ijkts} = \lambda_j .(P^D_{ik} - P^{es}_{ik} - LC^{DRP}_i .P^D_{ik}).\rho_i rt_{ijkts}, \quad \forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, t \in \Omega^{RT}, k \in \Omega^{Py}, s \in \Omega^s. \tag{5}$$

of electricity is shown as $\rho_i$.
Additionally, equation (7) is employed to estimate the overall cost associated with the integration of ESU. The addition of an incentive payment for utilizing the electricity of participating ESUs is particularly included in this equation. Furthermore, the calculation of $P^{es}_{ijkt}$ (equation 8) is performed to determine delivered active power to load point $i$. This calculation takes into consideration the charge and discharge performance rate ($\eta_{ch,dch}$) and state of charge of ESUs ($SOC^{es}_{ijk(t-1)}$) at load point $i$, contingency $j$, year $k$, and time $(t-1)$. To ensure the delivery of power to interrupted load points, it is necessary to determine the variable $SOC^{es}_{ijkt}$, which represents state of charge of ESUs at load point $i$ during contingency $j$, year $k$, and time $t$.
Furthermore, $CDRP$ (Cost of Demand Response Program) quantifies the net cost borne by the electric utility because of implementing $DRP$. Moreover, $CDRP$ is computed by

taking the difference between the incentive charges ($C_{ik}^{Inc}$) and the penalty charges ($C_{ik}^{Pen}$) in equation (9). The incentive charges represent payments made to Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

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$$rt_{ijkts} = \begin{pmatrix} t^{AS}.PTL_{ijkt}(DRP,ES) \\ +(1-P_{ijkt}^{es}/P_{ik}^{D}).(1-PTL_{ijkt}(DRP,ES)) \\ .t_{ijs}^{rep} \end{pmatrix} .\pi_{ij}^{AS} + (1-P_{ijkt}^{es}/P_{ik}^{D}).t_{ijs}^{rep}.(1-\pi_{ij}^{AS}), \quad \forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, t \in \Omega^{RT}, k \in \Omega^{Py}, s \in \Omega^{s}. \tag{6}$$

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$$TCES = \sum_{k\in\Omega^{Py}} \left(\frac{1}{1+Int}\right)^{k} \cdot \left[\sum_{i\in\Omega^{LP}} \sum_{j\in\Omega^{Cnt}} \lambda_j.\rho_{it}^{inc}.P_{ijkt}^{es}\right]. \tag{7}$$

$$P_{ijkt}^{es} = P_i^{cap}.\eta_{ch,dch}.(SOC_{ijk(t-1)}^{es} - SOC_{ijkt}^{es}) \quad \forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, t \in \Omega^{rt}, k \in \Omega^{Py}, s \in \Omega^{s}. \tag{8}$$

consumers who decrease their electric power usage as per their contractual agreement, while the penalty charges are imposed on customers who do not modify their consumption. The determination of $C_{ik}^{Inc}$ and $C_{ik}^{Pen}$ in equation (9) relies on equations (10) and (11) respectively. Equation (10) assumes that consumers will reduce their demand when a reduction signal is issued, although the magnitude of their response is uncertain. The probability of consumer response, denoted as $p_i^{Pr}$, is taken into account. Conversely, customers who do not respond to the reduction signal are subject to a penalty charge ($C_{ik}^{Pen}$) payable to the electric company. The probability of their non-response is represented by $q_i^{Pr}$. It is important to note that $p_i^{Pr}$ and $q_i^{Pr}$ are complementary numbers, as explained

$$CDRP = \sum_{k\in\Omega^{Py}} \begin{array}{c} \left(\dfrac{1}{1+Int}\right)^{k} .(1+q)^{k-1} \\ \cdot \left[\sum_{i\in\Omega^{LP}} (C_{ik}^{Inc} - C_{ik}^{Pen})\right] \end{array} \tag{9}$$

$$C_{ik}^{Inc} = p_i^{Pr}.P_{ik}^{D}.\sum_{j\in\Omega^{Cnt}} .\lambda_j.C_i^{inc}.LC_i^{DRP} \quad \forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, k \in \Omega^{Py}. \tag{10}$$

$$C_{ik}^{Pen} = q_i^{Pr}.P_{ik}^{D}.\sum_{j\in\Omega^{Cnt}} .\lambda_j.C_i^{Pen}.LC_i^{DRP} \quad \forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, k \in \Omega^{Py}. \tag{11}$$

$$q_i^{Pr} = 1 - p_i^{Pr} \qquad \forall i \in \Omega^{LP}. \tag{12}$$

$$C_i^{ink} = k_{ink} \times \rho_i \qquad \forall i \in \Omega^{LP}. \tag{13}$$

$$C_i^{pen} = k_{pen} \times \rho_i \qquad \forall i \in \Omega^{LP}. \tag{14}$$

in equation (12).

Additionally, the success of the suggested strategy is evaluated by employing the *SAIDI*, as mentioned in equation (15).

*SAIDI* serves as a reliability index to assess the average duration of interruptions experienced by the system. By monitoring *SAIDI*, the effectiveness of the suggested strategy in minimizing interruption durations and

$$SAIDI = \sum_{s\in\Omega^s} \pi_s . \left[ \left( \sum_{i\in\Omega^{LP}} \sum_{j\in\Omega^{Cnt}} \lambda_j . rt_{ijkts} . N_i \right) / \sum_{i\in\Omega^{LP}} N_i \right] \tag{15}$$
$$\forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, t \in \Omega^{rt}, k \in \Omega^{Py}, s \in \Omega^s.$$

enhancing system reliability can be evaluated.

### 2.2 Constraints

A number of technological and financial constraints are placed on the optimization task at hand. These constraints are encapsulated in the Linearized DistFlow equations, as illustrated in equations (16)-(19) [20]. At each node in the distribution system, equations (16) and (17) guarantee that active and reactive power are in balance. The voltage at each bus in the distribution system is determined by equations (18) and (19). Notably, the big-M technique is employed in these equations to handle the determination of voltages when a line is in an open condition. Equation (20) demonstrates that load flow through a line is contingent upon the switch condition (open or close) as well as the line's power capacity. Furthermore, Equation (21) highlights the requirement that during normal operation, the

$$P^D_{ikt} - P^{es}_{ijkt} - P^D_{ikt} . LC^{DRP}_i - P^{sub}_{kt} + \sum_{l\in\Omega^i} P^f_{lt} = 0 \tag{16}$$
$$\forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, t \in \Omega^{RT}, k \in \Omega^{Py}.$$

$$Q^D_{ikt} - Q^D_{ikt} . LC^{DRP}_i - Q^{sub}_{kt} + \sum_{l\in\Omega^i} Q^f_{lt} = 0 \tag{17}$$
$$\forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, t \in \Omega^{RT}, k \in \Omega^{Py}.$$

$$V_{mt} - V_{it} + \frac{r_l . P^f_{lt} + x_l . Q^f_{lt}}{V_1} \geq (\beta_{lt} - 1) . M, \tag{18}$$
$$\forall t \in \Omega^{TT}, i, m \in \Omega^{LP}, l \in \Omega^i.$$

$$V_{mt} - V_{it} + \frac{r_l . P^f_{lt} + x_l . Q^f_{lt}}{V_1} \leq (1 - \beta_{lt}) . M, \tag{19}$$
$$\forall t \in \Omega^{T}, i, m \in \Omega^{LP}, l \in \Omega^i.$$

$$-\beta_{lt} . cap_l \leq P^f_{lt} \leq \beta_{lt} . cap_l \tag{20}$$
$$\forall t \in \Omega^T, l \in \Omega^i.$$

$$\underline{V} \leq V_{it} \leq \bar{V} \tag{21}$$
$$\forall t \in \Omega^T, i \in \Omega^{LP}.$$

magnitude of the voltage at each bus must be within the standard range.

The active power capacity of the ESUs connected to power distribution network ($P^{es}_{ijkt}$) is constrained by maximum permissible power exchange. Equation (22), which represents this restriction, uses the terms $P^{ch,max}_i$ and $P^{dch,max}_i$ to denote maximum active power that ESU connected to load i is permitted to keep and inject, respectively. Furthermore, to safeguard the battery health and prevent deterioration in the ESU units, it is necessary to impose limits on the state of charge (*SOC*). This restriction is outlined in equation (23), with $SOC^{max}_i$ and $SOC^{min}_i$ denoting the ESU connected to load i's maximum and minimum permitted states of charge,

$$-P^{ch,max}_i \leq P^{es}_{ijkt} \leq P^{dch,max}_i \tag{22}$$
$$\forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, t \in \Omega^{rt}, k \in \Omega^{Py}.$$

$$SOC^{min}_i \leq SOC^{es}_{ijkt} \leq SOC^{max}_i \tag{23}$$
$$\forall i \in \Omega^{LP}, j \in \Omega^{Cnt}, t \in \Omega^{rt}, k \in \Omega^{Py}.$$

respectively.

The creation of a thorough model is one of this paper's major advances that accurately captures the behavior of customers as they consider participation in *DRP*s. This aspect of the paper is highly significant. The decision of customers to engage in *DRP*s is heavily influenced by the presence of incentives and penalties. Essentially, customers are reluctant to participate unless they are provided with a minimum incentive, accompanied by a continuous regime of penalties, such as the electricity price. The minimum incentive can be seen as the threshold for customers to join *DRP*s. As the incentive increases, customers become more willing to participate in *DRP*s, as long as their social welfare is not compromised. Thus, the number of participants in *DRP*s is greatly dependent on the levels of incentives and penalties. It is feasible to establish the ideal proportion of selected load that the firm should contract by modeling customer behavior from the viewpoint of an electric company, making sure that these quantities stay below the maximum value of consumers' *DRP* participating preferences. In other words, this inequality is taken into account in equation (24). $LC^{DRP}_i$ is reduced percentage of demand and

$$0 \leq LC^{DRP}_i \leq RL^{Max}_i, \tag{24}$$
$$\forall i \in \Omega^{LP}.$$

$RL^{Max}_i$ is max value of consumers' *DRP* participation.

## 3. Solution method

The 'Knapsack problem' is a well-known optimization issue that belongs to the class of mixed-integer non-linear programming. Solving this problem requires the application of metaheuristic algorithms, as mentioned in reference [21]. One such algorithm is the particle swarm optimization (PSO) method, which serves as a heuristic approach capable of simultaneously conducting global and local searches to achieve the best possible outcome. This structure, initially published [22], utilizes particles represented as $X_i$, which act as initial vectors. Each particle is assigned a speed vector ($V_i$) to guide its movement towards best local and global particles. The provided equation depicts

$$X^{k+1}_j = X^k_j + [V^k_j] \tag{25}$$

$$V_j^{k+1} = \omega^k \times V_j^k + c_1 \times r_1 \times (Pbest_j^k - X_j^k) + c_2 \times r_2 \times (Gbest^k - X_j^k) \quad (26)$$

process of upgrading these particles.
Within this equation, the term $\omega^k$ serves as an inertia weight, ensuring that each particle maintains its previous speed. The variable $Pbest_j^k$ represents the best recorded value of particle $j$ up until iteration $k$, while $Gbest^k$ signifies the best recorded value among all particles until iteration $k$. The properties of local and global optimum control are deduced using the constants $C_1$ and $C_2$, respectively. Additionally, the random values for the variables $r_1$ and $r_2$ range from 0 to 1.
The proposed strategy is visualized in Fig. 2 through a diagram representation. This approach involves studying the full contingencies of the optimization problem. The objective function aims to evaluate the optimal price, location, and amount of the participated load point $DRP$, as displayed in figure. The process is repeated until termination requirement is achieved, with new decisions made for price, location, and amount. In this case, the termination condition is based on a maximum number of iterations.

## 4. Test system and results

The suggested architecture's usefulness is demonstrated in this study through the application of a typical test scenario, namely Roy Billinton Test System (RBTS4). Fig. 3 presents a visual representation of the RBTS test system, while comprehensive system and component data, including failure rates and demand types, can be found in reference [23]. The study also incorporates network characteristics from [24] and simulation data from [25, 26], encompassing the price of energy for varying loads and the expenses of customer interruption for various consumer kinds. The test system is equipped with automatic switches and ESUs. Furthermore, the initial state of charge for the ESUs is assumed based on the findings in [4]. The planning horizon spans five years, with a fixed interest rate ($Int$) of 6% and an annual demand rise (q) of 3% throughout the planning horizon. As for the available automated switches and ESUs, reference [9] provides the necessary information, which is depicted in Fig. 3. The study calculates charging and discharging efficiency of ESUs to be 0.9. It is required that each bus maintains a maximum voltage of 1.05 p.u and a minimum voltage of 0.9 p.u. To model component repair time, reference [27] introduces the "log-normal distribution," which characterizes the dimensions of a probability density function curve with a bell shape. This distribution is specifically employed for lines and transformers, following the guidelines presented in reference [27]. The study considers various scenarios to address the uncertainty in repair time, using the Monte Carlo method. The simulation is run

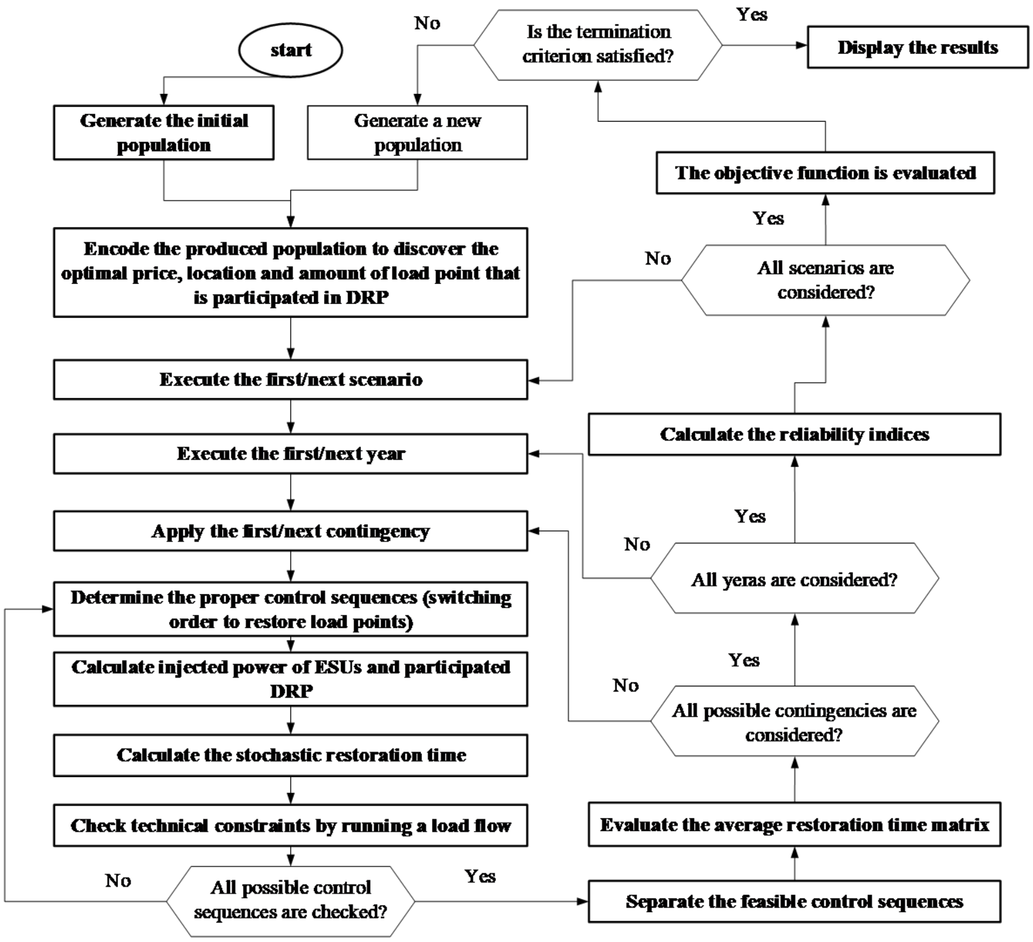


**Figure 2.** The proposed optimization algorithm's flowchart.

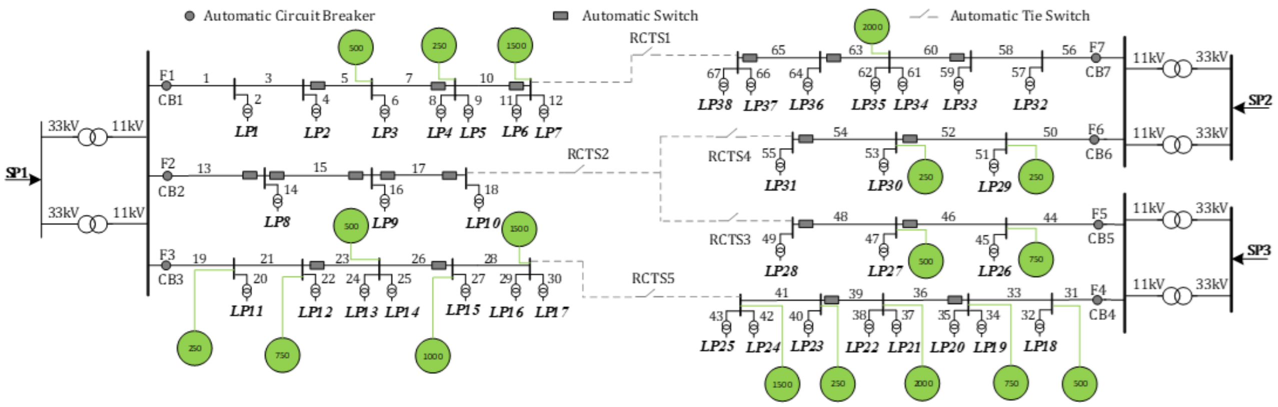


**Figure 3.** Test system equipped with automatic switches and ESUs.

a large number of times to generate different restoration time scenarios, with each scenario assigned a probability of 1/M. To manage the computational complexity, scenario reduction procedures are applied to retain the statistical characteristics of repair timeframes. The article explores the unpredictability of restoration time and selects five scenarios to capture the uncertainty. Table 1 provides details on these five Different Duration Tests (DDT) situations. The simulations are performed on a PC with an Intel Core i7 CPU @2.30 GHz and 8 GB RAM, using MATLAB to solve the proposed multi-objective nonlinear model.

Three different cases are explored to address the optimization problem. In Case I, an electrical distribution system is considered, which is equipped with automatic switches and ESUs but *DRP* is not taken into account. First case determines optimal values for *TC* and *SAIDI* as 1974.625 k$ and 2.2689 (hr./cust.yr.) respectively. Moreover, there are no load points located within the DPRP, resulting in a *CDRP* of 0 k$. The *TCIC* in this scenario amounts to 1746.252 k$. In continue, Case II focuses on an electrical distribution system with automatic switches and ESUs, emphasizing the identification of optimal load participation locations and amounts while considering a fixed price for *DRP*. In this case, the $k_{inc}$ and $k_{pen}$ are considered equal as 10, thus the $C^{inc}$ and $C^{pen}$ are 10 times the cost of energy. In Case II, the best values of *TC* and *SAIDI* are 1851.059 k$ and 2.0138 (hr./cust.yr.), respectively. Table 2 displays the location and *DRP* performance percent. As shown in this table, 17 buses are participated in *DRP*. in third case, Case III, it investigates an electrical distribution system with automatic switches and ESUs, aiming to identify the optimal load participation price, locations and amounts within a *DRP* framework. In this case, the $k_{inc}$ and $k_{pen}$ are variables and the solution algorithm tries to solve the problem with these variables. In this case, the optimum values of *TC* and *SAIDI* are 1745.413 k$ and 2.0133 (hr./cust.yr.) respectively. As shown in Table 2, 18 buses are participated in *DRP*. one bus is increased in *DRP*. As seen in Table 3, while the

**Table 1.** Probability and Repair Time.

| scenario | Repair time(lines) | Repair time (transformers) | probability |
|---|---|---|---|
| 1 | 4.702 | 5.348 | 0.209 |
| 2 | 3.181 | 6.41 | 0.249 |
| 3 | 4.827 | 6.965 | 0.136 |
| 4 | 4.356 | 8.91 | 0.292 |
| 5 | 3.449 | 5.065 | 0.114 |

**Table 2.** *DRP* Outcomes.

| | Location of *DRP* (bus number) | Amount of *DRP* (%) |
|---|---|---|
| Case II | 1-3-7-8-9-11-13-14-15-16-19-20-22-25-26-27-29 | 11-12-9-12-12-12-3-12-12-12-12-12-12-10-11-12-12 |
| Case III | 1-4-6-7-8-9-11-14-15-16-19-20-22-23-24-25-27-29 | 12-12-9-12-12-12-6-12-11-12-9-12-12-11-12-10-12-12 |

**Table 3.** All Cases Results.

| Cases | *TC*(k$) | $SAIDI(hr./cust.yr.)$ | *TCIC*(k$) | *TCENS*(k$) | *TCES*(k$) | *CDRP*(k$) | $k_{inc}$ | $k_{pen}$ |
|---|---|---|---|---|---|---|---|---|
| Case I | 1974.625 | 2.2689 | 1746.252 | 34.795 | 193.577 | 0 | 0 | 0 |
| Case II | 1851.059 | 2.0138 | 1454.186 | 28.763 | 193.577 | 174.532 | 10 | 10 |
| Case III | 1745.413 | 2.0133 | 1412.691 | 28.302 | 193.577 | 110.841 | 5 | 5 |

incentive and penalty cost for *DPR* are considered as variables, simultaneously, in contrast to Case II, the *TC* and *SAIDI* functions each saw a drop of 105.64 k$ and 0.005 hours annually. Additionally, the *TCIC* function shows a save of 41.49 k$ when compared to the prior instance. It follows that the optimal load participation price, locations and amounts within a *DRP* framework could reduce costs and *SAIDI*.
The main objective of this program is to optimize the utilization of non-sensitive (Domestic) load points by maximizing their capacity. However, in ”Case III,” there is a decrease in the number of non-sensitive load points from 11 to 9, while the number of sensitive (Commercial and Industrial) load points increases from 6 to 9. This change can be attributed to the reduced incentive and penalty cost associated with *DRP* in ”Case III” compared to ”Case II.” Consequently, the concentration of sensitive load points becomes more prominent. The provided table serves as a valuable guide for operator of power distribution network, offering information on the location and quantity of potential customers to consider when contracting a *DRP*. Moreover, Fig. 4 illustrates a significant reduction in the *CIC* for most loads in the third case, as opposed to the two previous cases. Although there is a minor increase in *CIC* for certain loads, the overall aggregation of *CIC* has decreased in recent situations due to significant drop in other loads. In addition, incentive for load points in Case II and Case III are shown in Fig. 5. As shown in this figure, total incentive cost in reduced because of decreasing the incentive price whereas the total cost is reduced.
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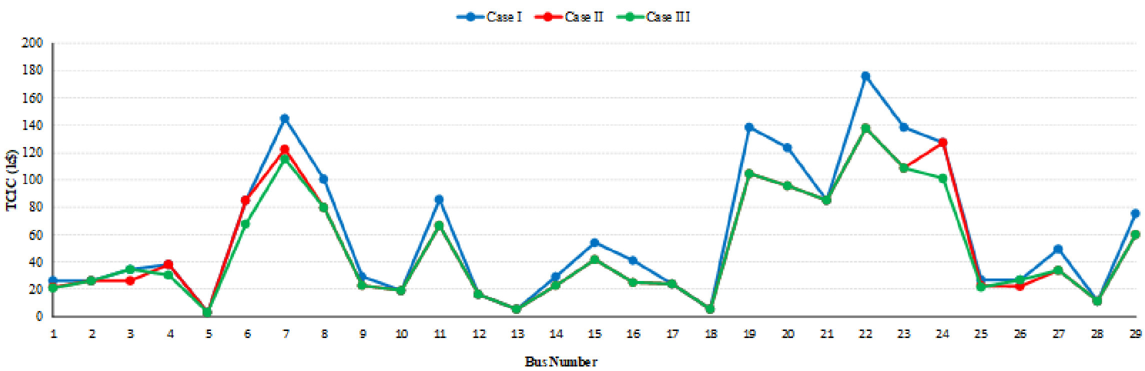


**Figure 4.** TCIC for the load points.

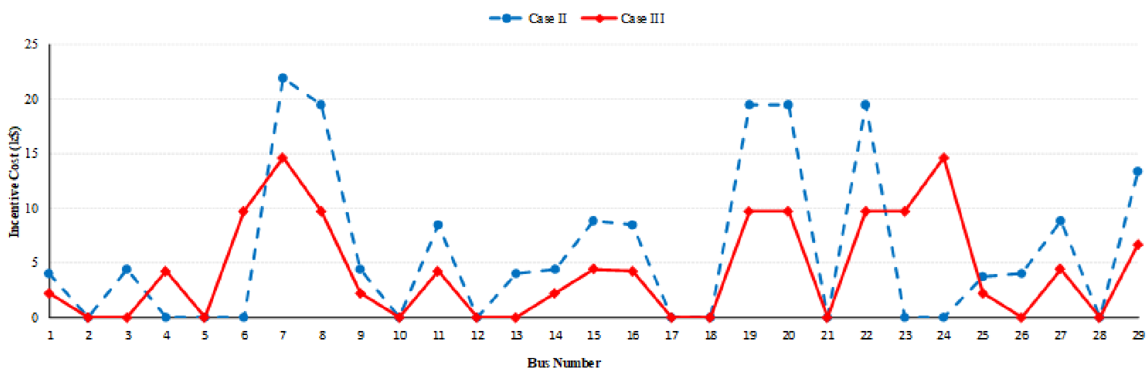


**Figure 5.** Incentives for load points in Case II and Case III.

**Table 4.** Sensitivity Analysis Results.

| $k_{inc}$ | $k_{pen}$ | *TC* (k$) | *SAIDI*(hr./cust.yr.) | *TCIC*(k$) | *TCENS*(k$) | *TCES*(k$) | *CDRP*(k$) |
|---|---|---|---|---|---|---|---|
| 5 | 1.66 | 1753.665 | 2.0431 | 1413.979 | 28.393 | 193.577 | 117.950 |
| 5 | 2.5 | 1751.499 | 2.0145 | 1413.898 | 28.342 | 193.577 | 115.681 |
| 5 | 5 | 1745.413 | 2.0133 | 1412.691 | 28.302 | 193.577 | 110.841 |
| 5 | 10 | 1731.548 | 2.0546 | 1408.154 | 28.584 | 193.577 | 101.232 |
| 5 | 15 | 1714.229 | 2.0426 | 1405.839 | 28.480 | 193.577 | 86.332 |

addition, incentive for load points in Case II and Case III are shown in Fig. 5. As shown in this figure, total incentive cost in reduced because of decreasing the incentive price whereas the total cost is reduced.

## 5. Sensitivity analysis of the incentive and penalty cost

As previously stated, the $k_{inc}$ and $k_{pen}$ are variables and the solution algorithm tries to solve the problem with these variables. The results of the $k_{inc}$ and $k_{pen}$ are 5 in Case III. In this section, a sensitivity analysis on the $k_{inc}$ and $k_{pen}$ is applied to examine influence of incentive and penalty costs on the obtains results. Table 4 shows the results of the different $k_{inc}$ and $k_{pen}$. In this case, the $k_{inc}$ is fix as a 5 and the $k_{pen}$ is changed as $(\frac{1}{3} \times k_{inc})$, $(\frac{1}{2} \times k_{inc})$, $(1 \times k_{inc})$, $(2 \times k_{inc})$, and $(3 \times k_{inc})$. The results show that when the $k_{pen}$ is increased the $TC$ and $TCIC$ is decreased because the participation of sensitive load (Commercial and Industrial) is increased. Sensitive loads are also having high amount and high interruption cost, thus the high participation of this type of load could decrease the $TCIC$ from 1413.979 k$ to 1405.839 k$ as 8 k$. therefore, the total cost of system is reduced because of large share of $TCIC$.

## 6. Conclusion

This paper presents a study on improving reliability in electrical distribution systems through the optimization of price, location, and the amount of participated load in a demand response program. The integration of automatic switches and ESUs in service restoration process is also taken into consideration. Additionally, uncertainty of restoration time for faulted equipment is addressed. The paper introduces a recommended objective function that aims to minimize the total cost of the system ($TC$), which includes several cost components such as cost of customer interruption, energy not supplied, ESU participation, and $DRP$. The results demonstrate that optimizing the incentive and penalty costs leads to significantly reduced $SAIDI$ index and total costs compared to scenarios with fixed prices and without $DRP$. Moreover, the value of the incentive and penalty costs is lower than the fixed ones in this study, resulting in increased participation of sensitive load points in $DRP$. Sensitivity analysis is conducted to measure the impact of incentive and penalty costs in $DRP$ on the efficacy of the aforementioned method. In summary, the implementation of demand response systems offers electric companies the chance to cut expenditures while simultaneously speeding up restoration in emergency instances.

**Authors contributions**
All authors have contributed equally to prepare the paper.

**Availability of data and materials**
The data that support the findings of this study are available from the corresponding author upon reasonable request.

**Conflict of interests**
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.



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