Robust Peak Reduction in Distribution Networks Using Traditional and IoT-Based Demand Response Resources

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Abstract: Peak demand management is a significant challenge for power grids, primarily due to constraints in generation capacity and rapidly increasing energy consumption. The emergence of new, energy-intensive loads, such as Bitcoin mining farms, has exacerbated the pressure on power utilities during peak demand periods. To address these challenges, demand response programs have emerged as practical solutions to mitigate peak load problems. This study investigates peak demand reduction through two demand response schemes: Time of Use (TOU), a traditional approach, and Automatic Demand Response (ADR), which has attracted increasing attention recently. Participants in these programs act as demand response resources for distribution companies (DisCos) in managing sustained peak loads. The TOU program is designed for elastic load customers, while ADR is applied to residential users and mining operations. The main contribution of this work is the development of a risk-based integrated scheduling model for Demand Response Resources (DRRs), designed to reduce peak demand cost-effectively across various operational tariff structures . These tariffs include price-based Time-of-Use (TOU) for price-sensitive aggregators and incentive-based ADR structures that provide compensation for residential and mining farm customers. Notably, the ADR strategy utilizes Internet of Things (IoT) technology to control household appliances and temporarily shut down cryptocurrency mining equipment. The proposed components are assessed using a detailed optimization model that accounts for the operator's robusteness toward renewable energy generation in the day-ahead scheduling process.

Keywords: *Demand response, ADR, Internet of Things, TOU, Cryptocurrency, Distribution Networks.*

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Nomenclature

Indices

i	Group I aggregators
j	Group II customers - residential
k	Group III customers – mining farms
t	Time
n	Cryptocurrency mining device
a	Class #1 home appliances
b	Class #3 home appliances

Parameters

ρ^{TRF}	Energy selling tariff defined by the DisCo
$\underline{E^{TOU}}, \overline{E^{TOU}}$	Energy consumption boundaries for TOU aggregator
Ξ	Baseline load
e_k	Price elasticity of aggregator
T^{out}	Outdoor air temperature
$\underline{T}, \overline{T}$	Comfort temperature range within the house
ϖ, σ	Coefficients defining the thermal characteristics of Class #2 appliances
$\underline{u^{c2}}, \overline{u^{c2}}$	Power consumption range of Class #2 appliances
R	Nominal power of devices
$\mathfrak{J}$	Consecutive operation time of Class #3 appliances
τ^s, τ^e	Permissible operating time range for Class #3 appliances
$\underline{R^{c4}}, \overline{R^{c4}}$	Power limits of Class #4 devices
$\eta^{\pm}$	Charge and discharge efficiencies of Class #4 devices
BC	Energy capacity of the PEV battery
$D(at, dt)$	D(at, dt): Distance traveled by the PEV between arrival time at and departure time dt

$\mathcal{M}$	Electric energy required per kilometer
λ^{II}	Incentive rate for Group II customers
ν	Indicates the percentage of cooling load to the mining load
MEN	Maximum event hours for Group III customers
ρ^{MF}	Mining electricity tariff
λ^{BTC}	Bitcoin price
ρ^{M}	Energy market price
μ	Bitcoin block reward
β_k	Hash rate of the mining device in farm k
δ	Bitcoin mining difficulty level
Υ	Hourly mining income
ξ	Uncertain variable
Γ	Robust control parameter
h_s, h_e	Start and end time of the peak reduction program
ξ^f	Compensation coefficient
$\psi_{j,t}^{MD}$	Hourly income from operating a mining device

Variables

x	Power contributed by DRRs of different groups
ρ^{TOU}	TOU price
γ	Load impact
T^{in}	Temperature inside the house
u	Power consumption of home appliances
z	Binary decision variable determining the operation time of devices and appliances
$\chi^{\pm}$	V2H PEV battery's charging and discharging powers
Q	Energy level of V2H PEV battery
Θ	Incentive payment
y	Auxiliary binary variable used for determining the event hours
$M_1. M_2, M_3$	Robust modeling auxiliary variables

1. Introduction

1.1. Automated Demand Response

As electric power systems evolve toward higher shares of renewable energy and smarter grid architectures, the role of demand-side flexibility becomes increasingly vital. Demand Response Programs (DRPs) have emerged as effective tools to balance supply and demand, reduce peak loads, and support grid reliability. These programs are typically classified into two main categories: price-based and incentive based mechanisms. Price-based programs rely on dynamic pricing schemes such as Time of Use (TOU), Real-Time Pricing (RTP), and Critical Peak Pricing (CPP) to influence consumer behavior by varying electricity prices based on temporal and market conditions. Notable examples include the work of Lu et al. [1], who developed a data-driven RTP model for industrial applications, and Ginigeme and Wang [2], who incorporated battery degradation into V2G strategies under RTP. Other studies, such as those by Yuan et al. [3], Moghimi and Barforoushi [4], and Zhang et al. [5], have explored the integration of real-time pricing into multi-regional systems, decision making for price-maker utilities, and reinforcement learning-based dynamic pricing, respectively. In contrast, incentive based programs offer financial rewards or direct control schemes to encourage load reduction during peak periods. These include Capacity Bidding Programs (CBP), Direct Load Control (DLC), and Demand Bidding Programs (DBP). Research in this area has examined various aspects such as game-theoretic modeling for distributed systems [6], smart home appliance scheduling [7], comparative analysis of TOU and RTP in hybrid microgrids [8], robust optimization frameworks for distributed generation [9], and energy storage management in islanded microgrids [10].

Building upon these conventional approaches, Automatic Demand Response (ADR) has recently gained attention as a next-generation solution. ADR systems employ advanced control, communication, and automation technologies to dynamically adjust electricity usage in response to utility signals without requiring manual intervention from end users. By enabling seamless, real-time load adjustments, ADR enhances the effectiveness, scalability, and responsiveness of DRPs, making them well suited for modern grid environments.

1.2. Key Features of ADR Programs

1- Automated Load Management

ADR programs streamline the reduction or shifting of electricity consumption through automation. Smart devices, sensors, and software are employed to automatically adjust the operation of appliances, HVAC systems, lighting, and industrial equipment in response to price signals, grid conditions, or direct commands from utilities or grid operators [11].

2- Real-Time Responsiveness

Designed for rapid and effective adaptation, ADR systems respond to real-time grid conditions, such as sudden demand surges or generation deficits. This capability ensures instantaneous balancing of supply and demand, reducing the risk of grid instability or blackouts.

3- Advanced Communication Infrastructure

ADR relies on sophisticated communication technologies to enable seamless interaction between consumers and grid operators. These systems support the remote execution of demand adjustments triggered by dynamic pricing or grid alerts, eliminating the need for manual interventions.

4- Tailored Load Control

ADR facilitates granular control of energy-consuming devices. In commercial settings, this may involve modifying HVAC temperatures or dimming lighting, while in industrial contexts, non-critical machinery can be temporarily deactivated. This level of customization allows for optimized energy usage with minimal disruption to operations.

5- Broad Sector Applicability

ADR programs are effective across residential, commercial, and industrial sectors. They can manage smart devices such as thermostats or water heaters in homes. In commercial and industrial settings, ADR optimizes the energy usage of large-scale equipment, including HVAC systems, refrigeration units, and production lines. By integrating these features, ADR programs play a pivotal role in modern energy management strategies, enhancing electricity consumption efficiency, reliability, and adaptability.

1.3. The Role of OpenADR in Advancing ADR Programs

OpenADR serves as a cornerstone in enabling efficient ADR programs, fostering a more sustainable and resilient energy system. As a communication protocol, OpenADR facilitates the automation of demand response events within electricity grids. It allows utilities and grid operators to transmit signals to energy management systems and devices, directing them to curtail electricity consumption during peak demand periods or in response to grid constraints. Developed by the OpenADR Alliance, the protocol is based on open, non-proprietary standards and is widely adopted in smart grids to enhance reliability, lower energy costs, and support the integration of renewable energy sources [12–17]. The research [18] underscores the critical role of communication technology and metering infrastructure in addressing the challenges of effective ADR implementation. Peer-to-peer (P2P) energy trading, facilitated by blockchain technology, has also been explored to improve security and overcome limitations in energy trading systems [19]. Additionally, machine-to-machine (M2M) technology has been utilized to automate price-based DRPs, particularly for commercial buildings [20].

The integration of machine learning techniques significantly enhances the implementation of ADR. Numerous studies have examined the application of machine learning to optimize DRPs and improve load forecasting tools. These efforts have been directed toward optimizing the scheduling of prosumers—energy producers who are also consumers [21]. For instance, reference [22] applied a model-free deep reinforcement learning (RL) approach to real-time ADR scenarios, while reference [23] developed an RL-based ADR program tailored to address congestion and voltage issues in distribution networks. Data mining and online learning techniques have also been employed to design optimal incentive schemes for ADR programs [24]. Furthermore, reference [25] proposed a cost-effective RL-based ADR framework utilizing an edge-cloud integrated solution.

1.4. Integrating OpenADR with IoT Technology

The integration of OpenADR with IoT technology enables precise energy usage control. IoT encompasses a network of physical devices embedded with sensors, software, and connectivity technologies that collect, exchange, and process data. These devices range from smart home appliances, such as thermostats and refrigerators, to industrial machinery and sensors in vehicles or power grids. IoT plays a pivotal role in the success of ADR programs by enabling automation, real-time communication, and precise control over energy consumption. By facilitating real-time data collection, automating energy adjustments, and ensuring seamless integration with smart grids, IoT technology strengthens the ability of ADR systems to minimize energy usage during peak periods. The combination of OpenADR and IoT underscores the transformative potential of modern energy management strategies, advancing grid efficiency and reliability.

1.5. Advancements in IoT-Based DRPs

The integration of OpenADR within IoT-enabled devices offers significant potential for reducing peak demand on the grid. This reduction translates into lower energy costs for consumers and improved grid stability and reliability. Moreover, it provides utilities and grid operators with an efficient platform for incorporating renewable energy sources, such as wind and solar, into the grid.

Recent studies have explored various facets of IoT-based demand response programs. For instance, research has focused on maximizing the profits of customers participating in IoT-based DRPs [26]. One study investigated peak load reduction using IoT-equipped home appliances and hybrid electric vehicles, supported by demand-side management software [27]. This research proposed an IoT-based demand response architecture featuring an appliance-aware recognition mechanism to optimize customer behavior during demand response events. Additionally, cutting-edge applications of IoT in intelligent water and energy management were examined [28]. Other research has addressed the broader aspects of IoT-based energy management, including The application of fuzzy comprehensive evaluation methods for industrial energy management [29].The architectural requirements and frameworks for energy management in smart buildings [30, 31].

The challenges and benefits of integrating IoT with smart city initiatives for efficient energy management [32].The design of management systems to enhance residential participation in IoT-based DRPs [33, 34]. Studies also detailed the architectural layers, advanced meters, and smart appliances essential for developing IoT-based home energy management systems. These investigations highlighted the role of Bluetooth Low Energy technology and fuzzy inference schemes in improving system efficiency [35]. Another study focused on managing peak demand in the residential sector through IoT-based demand response to alleviate distribution transformer loading issues. This research emphasized the classification of customers into critical and non-critical load points, as well as effective system monitoring [36]. Communication Technologies and Advanced Applications Narrowband IoT technology has been identified as an effective two-way communication solution for implementing ADR, as discussed in references [18, 37].

Additionally, a numerical search algorithm was proposed for optimizing energy consumption in IoT-enabled smart homes under price-based DRPs [38]. The performance and communication efficiency of IoT-based ADR systems, particularly for open-source platforms, were evaluated in [39]. Research also highlighted the integration of blockchain technology with OpenADR to enhance security and optimize peak management in IoT-based DRPs [40]. A cost-effective ADR scheme leveraging IoT to reduce cooling energy consumption in buildings with outdated air conditioning systems was introduced in [41]. Furthermore, [42] reviewed advanced applications of demand response in the industrial sector, focusing on the software and hardware requirements for IoT implementation, including mobile applications and smart devices. Reference [43] explored the framework of IoT-enabled smart grids, emphasizing the IoT's role in demand response and global strategies to enhance program effectiveness. Research [44] introduced a hybrid method for IoT-based energy management in smart grids that uses price-based demand response to enable continuous data monitoring and reduce power costs. Study [45] addressed peak management challenges and electric vehicle charging impacts through dynamic pricing strategies and IoT management of price-sensitive loads.

1.6. Future Prospects and Emerging Technologies

The role of 5G network infrastructure in IoT-based DRPs was explored in [46, 47], highlighting improvements in communication speed, reliability, and overall efficiency. Another study assessed customer readiness and the potential for green incentives to encourage participation in IoT-based demand response [48]. Reference [49] examined optimal architectural designs for implementing IoT-based demand response in campus microgrids, while [50] employed machine learning to analyze the participation of photovoltaic-integrated buildings in dynamic pricing schemes within IoT-based demand response frameworks. Additionally, authors in [51] presented an IoT-based smart energy management system using NodeMCU and Android platforms, allowing real-time monitoring of residential energy consumption and data collection on device usage.

These advancements underscore the transformative potential of IoT technology in enhancing the effectiveness, scalability, and sustainability of DRPs. By integrating IoT with protocols like OpenADR and emerging technologies such as 5G and blockchain, IoT-based DRPs are poised to play a pivotal role in modern energy management.

1.7. Cryptocurrency Mining and Its Impact on Distribution Networks

Cryptocurrency mining devices significantly contribute to the substantial peaks observed in power distribution networks. This energy-intensive process involves using powerful computers to solve complex mathematical problems, validate transactions on blockchain networks, and generate new cryptocurrency units as rewards. Due to intense competition, multiple miners often work simultaneously to solve the same problem, with the first to succeed earning the newly created cryptocurrency.

The appeal of digital currencies lies in their independence from traditional central banking systems. Bitcoin has achieved notable popularity among the various cryptocurrencies due to its open-source, peer-to-peer technology and reliance on a decentralized ledger or computer network. Mining Bitcoin, which requires solving intricate mathematical problems, demands processing power far beyond the capabilities of conventional computers.

The substantial energy consumption of cryptocurrency mining farms has been the focus of numerous recent studies, particularly regarding potential mitigation strategies through DRPs. Research [52,53] analyzed the integration of additional loads from cryptocurrency mining into the Texas power grid. This study examined the effects on the carbon footprint, grid reliability, and market pricing. A central aim was to evaluate various DRPs tailored for data centers, with an emphasis on estimating the annual revenues for mining facilities participating in these initiatives. In a related study [54], a novel energy management approach was proposed to simulate the impact of mining farms on the operation and efficiency of distribution networks. This research explored strategies to balance the high energy demands of mining operations with grid stability and efficiency. By incorporating demand response strategies, cryptocurrency mining facilities can play a more sustainable role in modern energy systems, mitigating their impact on peak loads while optimizing their operational costs.

1.8. Research Gap

Existing research in the field of demand response primarily focuses on the implementation of individual programs with various optimization objectives. However, studies that explore the integrated application of price-based and incentive-based programs are noteworthy. This integrated approach is particularly beneficial when adopted by the Distribution Company (DisCo) to reduce operational costs and peak load.

A careful review of previous research reveals a significant gap in the management of peak load in distribution networks, particularly concerning demand response resources (DRRs). This issue becomes critical as DisCos face an increase in capacity from digital currency miners, which contribute to substantial power consumption and elevate the peak load of the network. Effective management of DRRs—which are part of various DRPs and have distinct implementation tariffs—can play a crucial role in mitigating peak load. This challenge is exacerbated by the need to automate DRPs alongside traditional methods. Specifically, the integration of IoT technology in managing consumption is essential for enhancing the effectiveness of ADR initiatives. However, existing research often fails to address this topic in depth and lacks a comprehensive scheduling model for managing diverse DRPs. Additionally, the management of power consumption from mining farms within this integrated scheduling framework, particularly with the goal of reducing peak load, remains an important yet overlooked issue.

1.9. Main contribution

DisCos are responsible for reducing the peak load of the distribution network to a predefined target within a specified time frame during event days. As the electric industry transitions toward a national smart grid, automating DRPs using IoT technology has become imperative. Existing research underscores the importance of demand response and IoT in enabling program automation, with the primary challenge being the utility's ability to implement diverse DRPs for effective daily consumption management.

From the utility's perspective, the optimal outcome is achieved when customers actively participate in demand response initiatives, thereby minimizing costs and alleviating peak loads. This paper introduces a novel approach: optimal risk-based management of DRRs and distributed energy resources (DERs) to address intensive peak load challenges at the lowest operational cost. The central objective is to:

a) Determine the optimal dispatch of DERs.

b) Develop an advanced scheduling framework for IoT-enabled devices participating in ADR.

c) Design a multi-tier pricing structure for TOU customers to facilitate their interactions with the distribution network.

This comprehensive strategy aims to reduce peak demand cost-effectively. Figure 1 presents a graphic representation of the proposed peak load reduction framework.

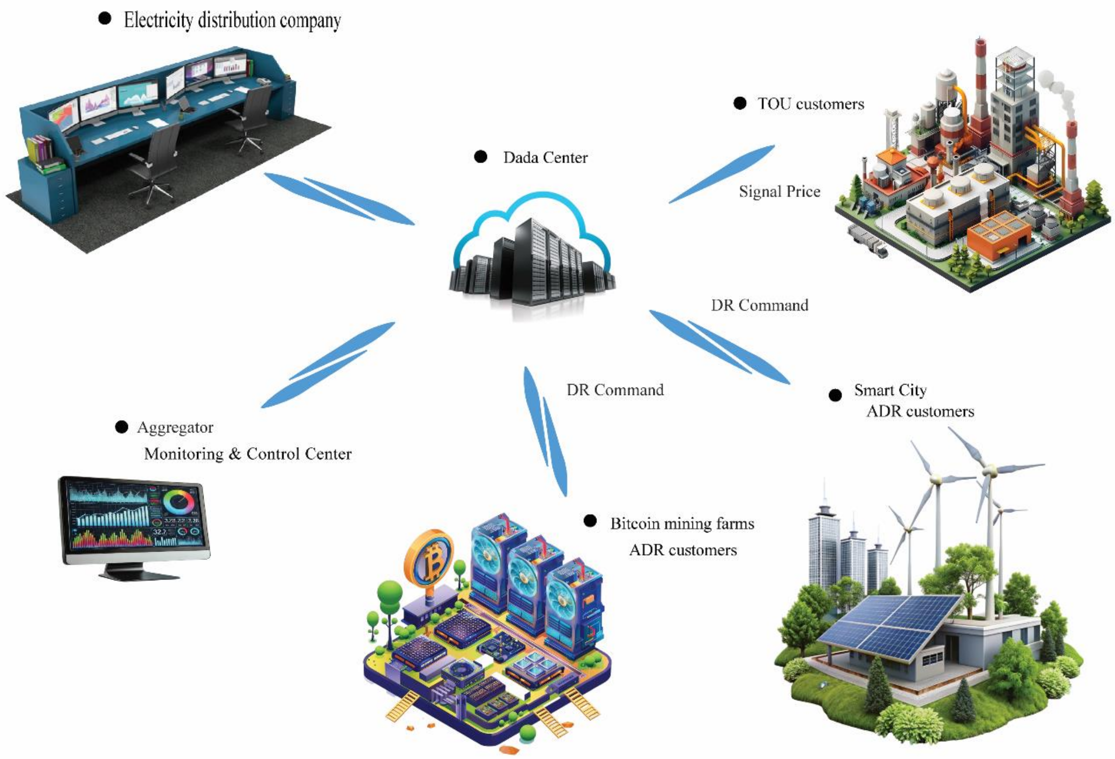

Fig. 1. Graphical diagram of the proposed integrated peak reduction architecture

The DRRs considered in this study include residential customers and cryptocurrency mining farms participating in ADR programs, as well as TOU program participants. The contractual terms differ between residential customers and mining farms within the ADR framework. Residential customers, for instance, seek attractive incentive payments, enabling the distribution operator to manage their electric appliance consumption through an IoT-based ADR system.

The ADR system classifies household appliances into four distinct groups based on their ability to respond to command signals, as detailed in Table 1. This classification enhances the precision and efficiency of load adjustments while ensuring customer satisfaction. Mining farms, on the other hand, operate under separate contractual terms, emphasizing operational efficiency and cost management. This innovative approach combines advanced scheduling, DER optimization, and tailored pricing mechanisms to enhance grid reliability and cost efficiency while addressing the challenges posed by peak demand.

Table 1- Classification of electric home appliances and devices

Class no	Appliance and device	Feature
#1	Television, computer, refrigerator, freezer, lighting	Non-programmable, uncontrolled, fixed load,
#2	Air conditioner, water heater, electric heater	Programmable, controlled, adjustable, and unshiftable load
#3	Washing machine, dishwasher, cloth dryer	Programmable, nonadjustable, shiftable load
#4	PEV (Plug-in Electric Vehicle), auxiliary battery energy storage	Programmable, controlled, adjustable, shiftable load

It has been observed that while appliances in Class #1 lack controllability and flexibility, the remaining classes demonstrate substantial potential for participation in the ADR program. By appropriately incentivizing customers, the Distribution Company (DisCo) can effectively reduce and shift loads by managing the usage of these appliances, ensuring benefits for both the utility and the customer. Mining farms also play a critical role in the ADR program, albeit with motivations distinct from residential participants. Mining devices consume significant amounts of electricity, making their management essential for alleviating peak loads. Encouraging mining farms to participate during high-stress periods can mitigate severe peak demands.

However, large-scale mining operations generate considerable rewards for farm owners, even with elevated electricity bills. Reducing the number of active mining devices imposes additional costs on utilities, as higher incentives are required to offset the losses incurred by these participants. To address this, contracts that compensate a substantial portion of the mining farms' lost rewards are deemed effective. These agreements incentivize participation by offering a more predictable economic outcome compared to the risk of unplanned rotating outages during peak periods. As a result, mining farms may prefer a modest reduction in profits through ADR participation over potential significant losses due to service interruptions. TOU pricing, a traditional demand response tool, allows utilities to engage flexible customers in managing peak demand. By implementing a multi-tiered TOU pricing structure, utilities can maximize load reductions during peak hours. Furthermore, renewable photovoltaic (PV) systems serve as valuable assets by contributing significant power capacity during summer peak periods within the distribution company's service area.

This paper introduces an optimal scheduling model designed for peak reduction, in which the DRRs are divided into three distinct groups, each with tailored participation mechanisms:

- ✓ Group I: Customers enrolled in the TOU program.
- ✓ Group II: Residential customers participating in the ADR program.
- ✓ Group III: Mining farm customers also engaged in the ADR program.

To mitigate peak loads on event days, the distribution operator requires a comprehensive day-ahead scheduling scheme for DRRs. This approach addresses the inherent uncertainty of PV generation by employing robust risk management techniques to account for potential solar power deficiencies during peak hours. The scheduling process involves programming the 24-hour operational states of IoT-enabled home appliances and mining devices, ensuring sufficient power capacity during critical periods while maintaining customer satisfaction. Unlike mining farms, residential appliance consumption patterns are determined based on historical data stored in cloud systems. This big data analysis enables the operator to define a specific energy baseline for individual ADR participants, facilitating the calculation of incentive payments proportional to baseline consumption on the event day. Key contributions of this paper are as follows:

- A robust peak reduction scheme through optimal day-ahead scheduling of DRRs.
- A 24-hour consumption program for IoT-enabled appliances of residential ADR participants.
- Programming the operational status of IoT-connected mining devices during peak reduction periods, with consideration for constraints and ADR participation contracts.

This framework presents a cost-effective and scalable solution for addressing peak load challenges while balancing utility objectives and customer engagement.

2. Methodology

The proposed scheduling problem focuses on peak reduction through the utilization of renewable energy resources and load response. The distribution company (DISCO) is tasked with optimal peak management, leveraging renewable resource assets and subscribers participating in DRPs. The problem involves various load response programs, with the objective function outlined in equation (1). This function consists of five components: the costs associated with purchasing power from Group I and Group II Demand Response Resources (DRRs), the expenses incurred for providing incentives to customers participating in the ADR program (including both Group II and Group III DRRs), and the revenue generated from selling the power contributed by DRRs to the upstream grid. This revenue is calculated based on the market price denoted by ρ_t^M. A detailed model of participation in the DRPs is provided below.

$$\begin{aligned}\min C = \sum_t \left(\sum_{i\in\Omega_i} \rho_{i,t}^{TOU} . x_{i,t}^{I} + \rho_t^{TRF} . \sum_{j\in\Omega_j} x_{j,t}^{II} \right) \\ + \sum_{j\in\Omega_j} \Theta_j^{II} + \sum_{k\in\Omega_k} \Theta_k^{III} \\ - \sum_t \rho_t^M . \left(\sum_{i\in\Omega_i} x_{i,t}^{I} + \sum_{j\in\Omega_j} x_{j,t}^{II} + \sum_{k\in\Omega_k} x_{k,t}^{III} \right)\end{aligned} \tag{1}$$

2.1. Group I DRRs

Constraints (2) to (4) define the power contributions of the Group I DRRs and their corresponding limitations. The parameter {B} represents the baseline load of the directly enrolled customer or aggregator i. Participating in the ToU program, calculated using historical consumption data from the past ten similar days. The hourly power contribution of the Group I DRRs is given by equation (2). The variable ρ^{ToU} denotes the real-time energy selling price ($/kWh) for the ToU participant on the event day, while the parameter ρ^{TRF} represents the energy tariff specified by the DISCO for the customers and ε refers to the price elasticity of the ToU participant. Constraint (3) restricts the expected energy consumption of the directly enrolled customer or aggregator in response to demand response calls. Additionally, the hourly load impact of the customer or aggregator is represented by γ, which provides a percentage measure of the participant's response and is proportional to the difference between the baseline load and the actual load on the event day, as indicated by equation (4). Load impact is an evaluation index used in the demand response context, and is defined as it is required in the result section. Negative values for the load impact indicate that the customer's consumption exceeds the baseline level.

$$x_{i,t}^{I} = \Xi_{i,t}^{I} . \left\{ 1 + \varepsilon_i \frac{\rho_{i,t}^{TOU} - \rho_t^{TRF}}{\rho_t^{TRF}} \right\} \tag{2}$$

$$\underline{E_i^{TOU}} \le \sum_{t=1}^{N_T} x_{i,t}^{I} \le \overline{E_i^{TOU}} \tag{3}$$

$$\gamma_{i,t} = x_{i,t}^{I} / \Xi_{i,t}^{I} \tag{4}$$

2.2. Group II DRRs

Group II Demand Response Resources (DRRs) contribute to grid stability by leveraging the automated response of residential customers participating in ADR programs. The scheduling of these DRRs is determined by the consumption characteristics of the involved appliances, which are Group into four classes, as shown in Table 1. Class #1 comprises rigid-load appliances, such as televisions and refrigerators, whose consumption remains fixed and cannot be adjusted or shifted to different periods. Class #2 appliances feature flexible consumption and can be programmed via an IoT interface, enabling their hourly load to be modulated within a specified range. Class #3 appliances are programmable to operate during off-peak hours on the event day. Class #4 devices, including plug-in electric vehicles (PEVs), are capable of both home-to-vehicle (H2V) and vehicle-to-home (V2H) operations. The batteries of these vehicles can be controlled through the IoT interface to charge or discharge at varying power levels during specified hours on the event day.

2.2.1. Class #2 appliances

The air conditioner is the only Class #2 appliance among the participating residential customers in this study. Its hourly output power can be adjusted by setting the internal temperature, represented by $T_{j,t}^{in}$, by the predefined program, as described in equation (5). shows the dynamic internal temperature and its variations in response to the ambient temperature and the power consumption of the HVAC system. The cooling power impacts the temperature through a negative coefficient σ. Therefore, the decrease in the internal temperature demands an increase in the power consumption. Index j refers to the residential customer participating in the ADR program. The internal temperature at time t is influenced by the external ambient temperature, the temperature at the previous timeslot, and the power consumed by the air conditioner, denoted by $u_{j,t}^{c2}$ .The superscript 'c2' indicates the appliance class. Constraints (6) and (7) limit the internal temperature and the power consumption of the air conditioner.

$$T_{J,t}^{in} = T_{J,t-1}^{in} + \varpi.\left[T_{J,t}^{out} - T_{J,t-1}^{in}\right] + \sigma.u_{j,t}^{c2} \tag{5}$$

$$\underline{T_j} \le T_{J,t}^{in} \le \overline{T_j} \tag{6}$$

$$\underline{u_j^{c2}} \le u_{j,t}^{c2} \le \overline{u_j^{c2}} \tag{7}$$

2.2.2. Class #3 appliances

Washing machines and dishwashers, which are classified under Class #3, are common household appliances that can participate in the ADR program. With the integration of IoT technology, these appliances can receive commands from the utility company specifying when the devices must be activated. In response to a demand response event, the appliance's operation is programmed to shift to a more suitable time of the day when the utility's operational costs are reduced, without compromising the resident's comfort. In essence, only the operation time of Class #3 appliances is adjusted for the resident, while the utility schedules the load shift to more cost-efficient periods, typically during off-peak hours. Constraints (8)-(10) define the operational limitations for these appliances on the event day.

$$u_{j,b,t}^{c3} = z_{j,b,t}^{c3} . R_{j,b,t}^{c3} \tag{8}$$

$$\sum_{t=\tau_{j,b}^{s}}^{\tau_{j,b}^{e}} z_{j,b,t}^{c3} = \Im_{j,b} \tag{9}$$

$$z_{j,b,t'}^{c3} - z_{j,b,t'-1}^{c3} \le \left[\sum_{t=t'+1}^{t'+\Im_{j,b}} z_{j,b,t}^{c3}\right] \Big/ \left[\Im_{j,b} - 1\right] \tag{10}$$

Equation (8) adjusts the utilization time of appliance b from Class #3 using the binary variable z. This decision variable determines whether an appliance, such as a washing machine, can operate during a specific time slot t. Consequently, the hourly load of the IoT-equipped appliance is represented by $u_{j,b,t}^{c3}$, which corresponds to the appliance's nominal kW consumption. Equation (9) defines the operating duration of the appliance, which is primarily influenced by the resident's habits. However, these appliances must operate continuously for the specified duration without interruption, as stated in constraint (10).

2.2.3. Class #4 appliances

Energy storage devices, such as hydrogen energy systems and PEVs with rechargeable batteries used for propulsion, are Group as Class #4 appliances. Residential customers with PEVs can upgrade their vehicles to controlled-charging electric vehicles through an IoT interface. This integration enables the PEV to communicate with the resident and monitor the battery's state of charge (SoC), whether the vehicle is stationary or in motion, to determine the most efficient charging time and rate. Additionally, IoT technology can facilitate communication between PEVs and other vehicles, as well as traffic management systems, to optimize traffic flow and alleviate congestion.

For IoT-enabled PEVs participating in the ADR program, the distribution operator can adjust their charging and discharging schedules based on grid demand and the customer's driving patterns. The V2H capability, in addition to the H2V function, allows the PEV, when parked and plugged into the home, to supply discharge power during peak times according to a pre-established day-ahead program. The performance of these IoT-enabled PEVs, both in parked (plugged-to-home) and driving modes, as well as their participation in ADR, are constrained by the following conditions (11)-(17).

$$u_{j,t}^{c4} = \chi_{j,t}^{+} - \chi_{j,t}^{-}, \forall S_{j,t} = 1 \tag{11}$$

$$S_{j,t}.z_{j,t}^{c4,+}.\underline{R_j^{c4}} \le \chi_{j,t}^{+} \le S_{j,t}.z_{j,t}^{c4,+}.\overline{R_j^{c4}} \tag{12}$$

$$S_{j,t}.z_{j,t}^{c4,-}.\underline{R_j^{c4}} \le \chi_{j,t}^{-} \le S_{j,t}.z_{j,t}^{c4,-}.\overline{R_j^{c4}} \tag{13}$$

$$Q_{j,t} = Q_{j,t-1} + \frac{\eta_j^{+} \cdot \chi_{j,t}^{+}}{BC_i} - \frac{\chi_{j,t}^{-}}{\eta_j^{-}.BC_i}, \forall S_{j,t} = 1 \tag{14}$$

$$Q_{j,at} = Q_{j,dt} + D_j(at,dt).\mathcal{M}_j.S_j \quad \forall\{S_{j,t} = 0 \;\&\; at \le t \le dt\} \tag{15}$$

$$\underline{Q_j} \le Q_{j,t} \le \overline{Q_j} \tag{16}$$

$$\chi_{j,t}^{+} + \chi_{j,t}^{-} \le 1 \tag{17}$$

Equation (11) defines the power flow between the home and the PEV, controlled through the IoT. This flow can either be a positive signal for charging the vehicle or a negative signal for discharging power. This is applicable only when the PEV is parked and plugged into the home, denoted by $S_{j,t} = 1$. A zero value for this binary parameter indicates that the PEV is in driving mode. Equations (12) and (13) constrain the charging and discharging power. Equation (14) updates the State of Charge (SoC) of the PEV battery at each time slot based on the charging and discharging power specified in the program. The change in SoC over the driving distance is described by equation (15), where at and dt represent the departure and arrival times, respectively. The SoC of the PEV must remain within a permissible range, as specified in equation (16). Additionally, during the plug-in mode, the PEV battery must be in one of the three states: charge, discharge, or idle, as defined in equation (17). Taking into account the appliance classes and their programming model, the residential customer's load response to the ADR command is represented by equation (18). Note that $R_{j,a,t}^{c1}$ (in kW) refers to the rated consumption of Class #1 appliances, which do not respond to ADR commands. The reduced load, representing the procured power from the Group II DRR, is denoted by $x_{j,t}^{II}$, calculated as the difference between the customer's baseline load and the impacted load $u_{j,t}$, as shown in equation (19). The baseline load $\Xi_{j,t}^{II}$ is computed in equation (20) by summing the loads of all appliances from Class #1 to Class #4, in the absence of any event day call. Moreover, the incentive payment to the participating customer is determined by equation (21). Under the terms of the ADR program contract, the distribution company is required to pay an incentive according to the reduced kW and a specific incentive rate ($/kWh).

$$u_{j,t} = \sum_a R_{j,a,t}^{c1} + u_{j,t}^{c2} + \sum_b u_{j,b,t}^{c3} + u_{j,t}^{c4} \quad (18)$$

$$x_{j,t}^{II} \geq \Xi_{j,t}^{II} - u_{j,t} \quad (19)$$

$$\Xi_{j,t}^{II} = \sum_a R_{j,a,t}^{c1} + R_{j,t}^{c2} + \sum_b R_{j,b,t}^{c3} + R_{j,t}^{c4} \quad (20)$$

$$\Theta_j^{II} = \sum_t \lambda^{II} . x_{j,t}^{II} \quad (21)$$

2.3. Group III DRRs

Mining farms play a significant role in increasing the peak demand on distribution networks. Encouraging farm owners to participate in the ADR program can help alleviate the impact of high peak loads and reduce operational costs for distribution operators. In these farms, command-line interfaces (CLIs) are commonly used to manage and configure mining hardware and software. CLIs, as text-based interfaces, allow users to interact directly with the mining device's operating system. As a result, control over mining devices can be executed by the distribution operator through the CLI, enabling farm owners to participate in the ADR program. Typically, mining farms are organized into multiple lines, each containing a set number of mining devices. These lines can be controlled individually through an IoT interface, such as an Arduino device, thereby reducing the costs associated with ADR infrastructure. Moreover, in response to ADR events, mining farms can reduce power consumption by temporarily interrupting some of the mining devices. This is demonstrated in Figure 1, where a master controller sends command sets to the IoT controllers of each mining line. These slave controllers issue binary 0/1 signals to the mining devices, instructing them to either interrupt or continue operation. This structure enables the distribution operator to manage the farm's energy consumption under the IoT-enabled ADR program, by the following constraints.

This rephrasing uses formal academic language while preserving the technical accuracy of the original content.

$$x_{k,t}^{III} = \frac{1}{1 - \nu_k} \sum_{n \in \Omega_{k(n)}} z_{k,n,t}^{CMD} . R_{k,n}^{CMD} \quad (22)$$

$$\sum_{n \in \Omega_{k(n)}} z_{k,n,t}^{CMD} \leq \alpha . \left|\Omega_{k(n)}\right| \quad (23)$$

$$\frac{1}{\left|\Omega_{k(n)}\right|} \sum_{n \in \Omega_{k(n)}} z_{k,n,t}^{CMD} \leq y_{k,t} \leq \sum_{n \in \Omega_{k(n)}} z_{k,n,t}^{CMD} \quad (24)$$

$$\sum_{t=h_s}^{h_e} y_{k,t} \leq MEN \quad (25)$$

$$\Upsilon_{k,t}^{CMD} = \lambda^{BTC} . \left(\frac{3600_{sec} . \beta_k . \mu}{\delta . 2^{22}} \right) \quad (26)$$

$$\Theta_k^{III} = g^{MF} . \sum_t \left(\sum_{n \in \Omega_{k(n)}} z_{k,n,t}^{CMD} . \Upsilon_{k,t}^{CMD} - \rho^{MF} x_{k,t}^{III} \right) \quad (27)$$

The index of mining farms participating in the ADR assumes that each mining device n has a rated power consumption represented by $R_{k,n}^{CMD}$ (kW). For a set of mining devices $\Omega_{k(n)}$ Within farm k , the farm's provided power to the grid in response to the ADR call is represented by $x_{k,t}^{III}$, which can be known as the output power of a Group III DRR (22). The binary decision variable $z_{k,n,t}^{CMD}$ Determines whether the mining device n is interrupted ($z = 1$) or not. The distribution operator is allowed to dispatch the interruption command to a maximum of α % of the maximum number of mining devices. $\left|\Omega_{k(n)}\right|$ At each hour (23). The number of ADR calls by the operator to the farm's demand reduction on an event day is limited to MEN , based on (24) and (25). The ADR calls must be within the peak reduction scheme duration [h_s, h_e], and y is an auxiliary binary variable.

The income generated from operating a mining device for one hour and producing Bitcoin is represented by equation (26), which is directly influenced by the device's hash rate. Additionally, mining income is significantly affected by factors such as the daily Bitcoin price and the mining difficulty level. Consequently, the difference between income and operational costs determines the profit earned by the mining farm. However, this profit may become negative due to factors like a low hash rate, a decrease in Bitcoin price, or an increase in mining difficulty, which may lead the farm to suspend mining activities during that particular hour. The incentive payment structure proposed in this paper is described in equation (27). Under the ADR program, the electric utility is responsible for compensating the farm owner for any financial losses incurred as a result of participating in the program. The compensation is calculated using a percentage coefficient, which can range from 0.9 to 1.05. It is essential to note that the consumption cost is determined based on the mining tariff set by the distribution utility.

2.4. Peak reduction under robust approach

The distribution operator plays a vital role in reducing peak load within the designated territory. Their primary objective is to lower the peak load to a specific target level during a predetermined peak period, utilizing renewable-based DERs and DRRs. Inequality (28) specifies that the total scheduled power from the DRRs and DERs during the contracted period must exceed the difference between the grid's baseline demand and the established peak level. This peak level is determined by the hierarchical system operator, who is responsible for overseeing generation adequacy and ensuring the security of the transmission system. The operator's role is to ensure that peak reduction is carried out efficiently while minimizing the associated cost of the event day, represented by τ_s, τ_e .

$$\sum_{i \in \Omega_i} x_{i,t}^{I} + \sum_{j \in \Omega_j} x_{j,t}^{II} + \sum_{k \in \Omega_k} x_{k,t}^{III} + \xi_t^{PV} \geq \xi_t^{ND} - \psi_t \, , \quad \forall \tau_s \leq t \leq \tau_e \quad (28)$$

The uncertainty associated with photovoltaic (PV) generation within the distribution company's service area presents a significant challenge for the distribution operator. Inaccurate predictions of PV generation can lead to power shortages during peak demand periods, resulting in additional costs for the operator due to the need for load shedding. To manage this uncertainty, the operator can adopt a robust strategy based on robust optimization. This mathematical technique is designed to handle variability and uncertainty within a system, making it especially useful in decision-making situations where parameters are uncertain. Unlike traditional optimization, which aims to find the optimal solution based on fixed parameters, robust optimization acknowledges that these parameters are often imprecise and can fluctuate within specific ranges. This uncertainty can impact the feasibility and optimality of proposed solutions, making robust optimization a valuable tool for managing uncertainty in energy distribution.

Robust programming addresses this uncertainty by considering the worst-case scenario of parameter variations. Rather than seeking a single optimal solution, it aims to find one that performs well across all possible realizations of uncertain parameters within their defined bounds. Suppose the PV generation during peak hours is an interval-based uncertainty parameter that lies within the boundary of $P_t^{PV,min} \le P_t^{PV} \le P_t^{PV,max}$. The distribution operator's conservative approach can be incorporated into the peak reduction scheme by reformulating constraint (30) into constraints (32)-(34). In these three constraints, Γ represents the robust control parameter, which dictates the risk strategy of the distribution operator. $\Gamma = 0$ represents the operator’s risk-neutral attitude, while $\Gamma = 1$ indicates a risk-averse strategy. Additionally, the three positive variables M_1, M_2, and M_3 serve as auxiliary variables to model the robust counterpart of the deterministic problem [55].

$$\sum_{i\in\Omega_i} x_{i,t}^{I} + \sum_{j\in\Omega_j} x_{j,t}^{II} + \sum_{k\in\Omega_k} x_{k,t}^{III} + \left(\xi_t^{PV} - M_1^{PV}.\Gamma - M_{2,t}^{PV}\right) \ge \left(\xi_t^{ND} + M_1^{ND}.\Gamma + M_{2,t}^{ND}\right) - \psi_t , \qquad \forall h_s \le t \le h_e \tag{32}$$

$$CapM_1^{PV} + M_{2,t}^{PV} \ge \left(\overline{\xi_t^{PV}} - \underline{\xi_t^{PV}}\right).M_{3,t}^{PV} \tag{33}$$

$$M_1^{ND} + M_{2,t}^{ND} \ge \left(\overline{\xi_t^{ND}} - \underline{\xi_t^{ND}}\right).M_{3,t}^{ND} \tag{34}$$

$$M_1^{PV}, M_{2,t}^{PV}, M_1^{ND}, M_{2,t}^{ND} \ge 0, M_{3,t}^{PV}, M_{3,t}^{ND} \ge 1$$

3. Input data, simulation results, and discussions

3.1. Input data

This section presents the simulation results to assess the accuracy of the previously discussed programming model. The simulation was carried out in a specified test region within the electric service area of a distribution company. The region includes five aggregators participating in the TOU program, fifty residential customers with ADR capabilities, two mining farms also equipped with ADR capabilities, and other standard customers without demand response agreements. Table 2 provides the price elasticity values for the five aggregators in the TOU program. To further illustrate the data, Fig. 2 depicts the baseline load of these aggregators, highlighting both the peak baseline load (a) and the corresponding 24-hour demand factor.

Table 2- Equivalent price elasticity of the aggregators that participated in the TOU

Aggregator no	1	2	3	4	5
Price elasticity	-0.4	-0.45	-0.3	-0.27	-0.36

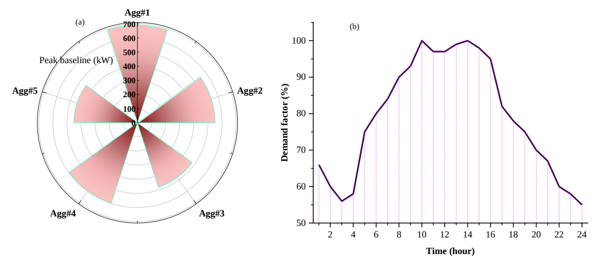

Fig. 2. Peak baseline and 24-hour demand factor of the aggregators participating in the TOU

Table 3 provides essential information about the IoT-connected air conditioners utilized by these customers, including the power range, desired temperature range, and the beta (β) coefficient, where negative values correspond to the cooling function. The alpha (α) parameter is consistently set to 0.9 across all groups. Additionally, Table 4 outlines key details for the IoT-integrated PEVs, including battery power rating, energy capacity, efficiency, time spent away from home, and route length for each vehicle. All PEVs feature H2V and V2H capabilities. The batteries of these vehicles are assumed to consume 428.8 W of power per mile traveled. According to the electric utility’s regulations, residential customers participating in the ADR program are entitled to a $2 incentive for every kWh reduction in their energy consumption.

Table 3- Usage characteristics related to air conditioners of different consumption patterns

Consumption pattern	1	2	3	4
Min/Max power (W)	500/1800	600/2400	700/3000	800/4000
Min/Max temp (℃)	16/24	15/25	17/25	16.5/24
β	-0.009	-0.010	-0.0085	-0.011

The electric service area includes two active bitcoin mining farms, with key details presented in Table 5. The analysis shows that the first farm has opted for a larger quantity of lower-cost mining devices, while the second farm utilizes fewer, but more powerful devices that offer a higher hash rate, resulting in greater mining efficiency. Data from [56] dated jan 29, 2024, indicates that the price of Bitcoin is $102,871.18,.

As outlined in the ADR contract, the DisCo is authorized to interrupt up to 160 mining devices at the first farm and 120 devices at the second farm during specified event days. The contract stipulates that the DisCo may issue interruption notifications with a maximum lead time of 4 hours during peak management periods on these event days. Furthermore, the contract ensures that the DisCo will compensate the farms for 95% of the revenue lost due to their participation in the ADR program on these designated event days.

The peak reduction scheme of the DisCo is scheduled to begin at 11:00 a.m. and conclude at 7:00 p.m. on the designated event day. The electric service area is expected to experience a pure demand during this period, as shown in Figure 3. The projected aggregated PV generation output for the entire duration, from 7:00 a.m. to 7:00 p.m., on the event day is also illustrated in Figure 3. The system operator has informed the distribution operator of the requirement to reduce peak demand in the area to 10,100 kW from 11:00 a.m. to 3:00 p.m., and to 10,400 kW from 4:00 p.m. to 7:00 p.m., based on working assumptions. Additionally, the 24-hour market prices, forecasted and sourced from IREMA, Iran's compatible energy market [56], are depicted in Figure 4 and compared with the approved three-tiered energy selling tariff for customers.

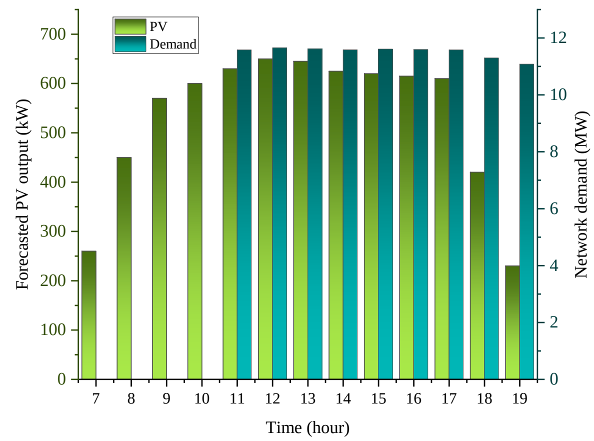

Fig. 3. Forecasted power of PV during hours 7-19

Table 4 - Required data on PEVs

Pattern number	Power rate (kW)		Max capacity (kWh)	Battery efficiency (%)		In movement status of PEV	
	Min	Max		Charge	Discharge	Time (hour)	Path length (km)
1	0.2	3.0	10	93	90	11 to13	2.4
2	0.3	4.0	16	95	92	17 to 20	3.3
3	0.15	3.2	12	94	91	18 to 22	4.2
4	0.1	2.5	16	97	93	9 to 12	2.9

Table 5- Required data on the mining farms

Farm number	Mining devices model	Hash rate (Th/sec)	power (kW)	Price ($)	Number of devices
1	Bitmain Antminer T19	84	3.150	2,000	300
2	MicroBT Whatsminer M50S	126	3.276	3,500	200

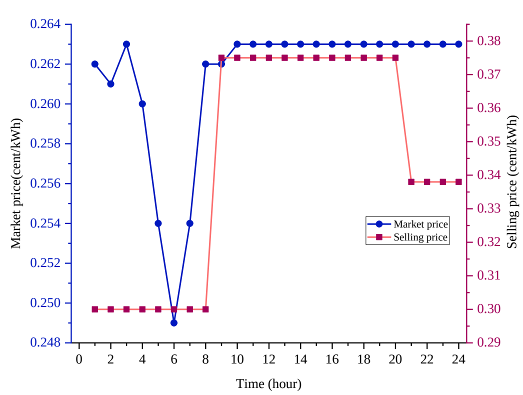

Fig. 4. Forecasted day-ahead market price and selling energy price

A The simulation was performed on a laptop with a Core i7 processor and 8GB of RAM. GAMS software was used to execute the simulation, with solutions generated through the CPLEX solver. To facilitate a thorough analysis and validation of the proposed model across various scenarios, two distinct case studies were created.

3.2. Case Study 1:

The first case study investigates the deterministic model for peak load reduction within the designated test service area. Implementing this strategy for the event day results in an estimated cost of $2,456.64 for the distribution company. The ex-ante response of the five aggregators participating in the TOU program is presented in Fig. 5. The positive response values recorded during peak hours, as shown in the figure, demonstrate the effective load reduction achieved by these aggregators. At 2:00 p.m., these five Demand Response Resources (DRRs) collectively achieve a total power reduction of 354.92 kW, marking the highest reduction across the event day. Notably, the aggregators exhibit negative response values between 6:00 a.m. and 10:00 a.m., as well as after 8:00 p.m. during the night. This suggests that customers enrolled in these aggregators are encouraged to increase their energy consumption relative to the baseline during these off-peak periods..

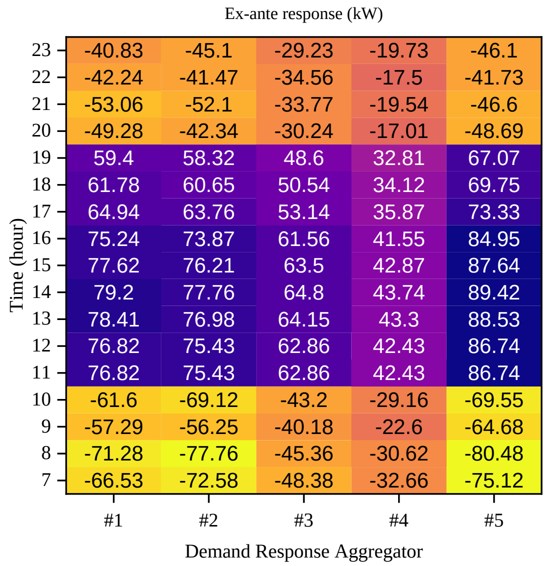

Fig. 5. Ex-ante response of the aggregators during the event day

Additionally, the second aggregator, which demonstrates a higher elasticity to price fluctuations, is expected to have the most significant load impact, reducing demand by 16.20% on the event day. Figure 6 shows the corresponding variations in energy selling prices, integrated into the TOU pricing structure for the aggregators. Customers associated with the second aggregator, who experience the largest load reduction during peak hours, encounter a notable increase in prices during these periods due to their higher elasticity and greater potential for load shifting compared to the other aggregators. The figure also compares the four-tier TOU pricing scheme to the standard tariffs applied on regular days for conventional customers. With the exception of the early morning hours (1-6 a.m.), prices have dropped between 7 a.m. and 10 a.m., creating an opportunity for increased consumption among customers enrolled in the second aggregator's program.

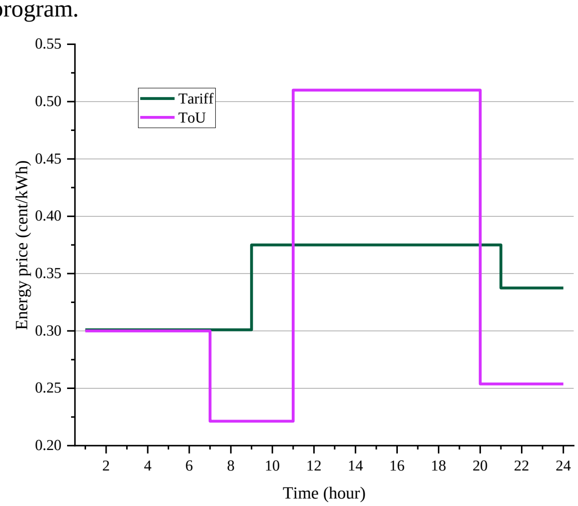

Fig. 6. TOU energy price besides the company's tariff

Figure 7 illustrates the total power capacity delivered by Group II DRRs on an hourly basis during the designated peak reduction period on the event day. These resources were programmed to participate in the peak load reduction for a total of 8 hours. At 18:00, they contribute 203.16 kW of power, which accounts for 22.57% of the required power to reduce the peak load below the set threshold.

It is noteworthy that the operator chose to temporarily suspend the power contribution from the Group II DRRs for one hour, from 16:00 to 17:00. This decision was made due to the limited energy capacity of these resources and the operator's focus on maximizing power contributions during the critical time slots of 15:00 and 18:00. Consequently, the power required to reduce the peak load at 16:00 was effectively sourced from the resources in Groups I and III.

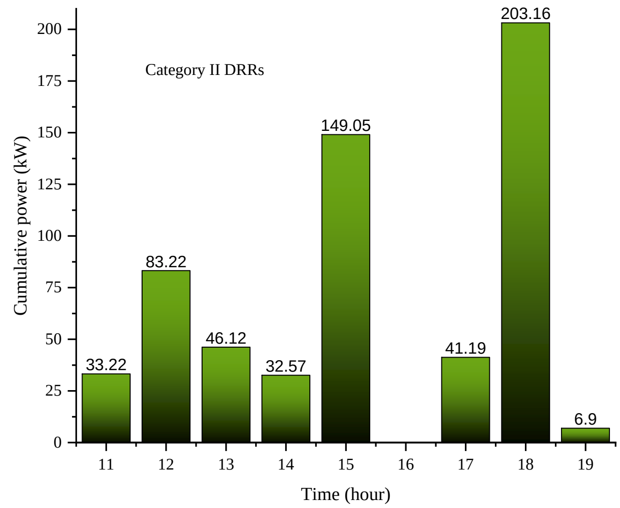

Fig. 7. Expected hourly cumulative power contributed by Group II DRRs.

Figure 8 illustrates the power profile of the PEV batteries throughout the event day, based on data from all 50 residential customers. Notably, the PEVs are charged during off-peak hours, which helps increase the state of charge (SoC) of the batteries, enabling them to provide both driving and discharge power during peak periods. Additionally, the discharge power from the PEV batteries, utilizing the V2H feature, is predominantly concentrated between 12:00 p.m. and 5:00 p.m. The total amount allocated for incentive payments to these customers is $1,191.70.

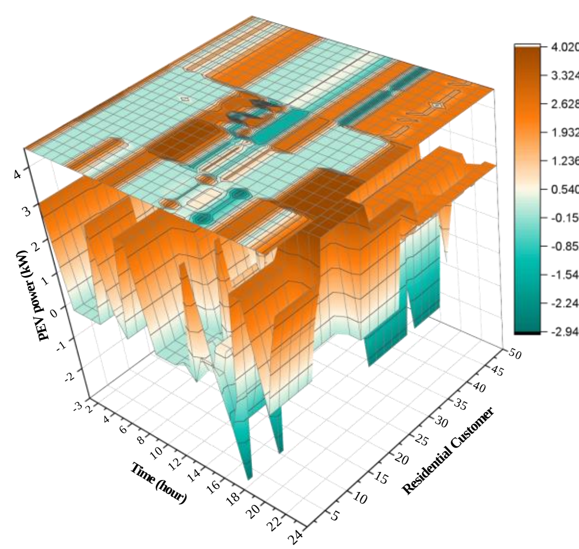

Fig. 8. Expected charge and discharge power of PEVs

Table 6. Expected power contributed by the Group III DRRs

	Time (hour)							
	11	12	13	14	15	16	17	19
Farm #1	472.50	472.50	472.50	472.50	×	×	×	×
Farm #2	×	×	×	×	393.12	242.42	239.14	176.90

The ADR program also includes mining farms as participants. Table 6 details the scheduled power contributions from two Group III DRRs during the peak reduction plan on the event day. Notably, the first mining farm has a higher power capacity compared to the second. Both farms are committed to four hours, as specified by the contract. Since the operator did not configure the Group II DRRs to supply power between 4:00 and 5:00 p.m., the second mining farm is responsible for providing 43.68% of the required power for peak reduction during this time. In line with the contract terms, the distribution company is required to provide the first mining farm with an incentive payment of $791.73. In contrast, the second farm, which has fewer mining devices and faces more restrictions on device interruptions, is awarded a lower incentive payment of $478.03.

3.3. Case study 2

The earlier case study effectively showcased a deterministic method for peak load reduction, with the distribution operator fully aware of the inherent risks. In contrast, this case study takes a risk-based approach to evaluate the proposed peak reduction strategy. We utilize the robust approach to efficiently schedule the optimal DRRs, particularly focusing on PV generation. Figure 9 presents the prediction interval for the PV generation within the service area during the peak hours. This interval serves as a representation of the potential range of values in which the actual PV generation may fluctuate.

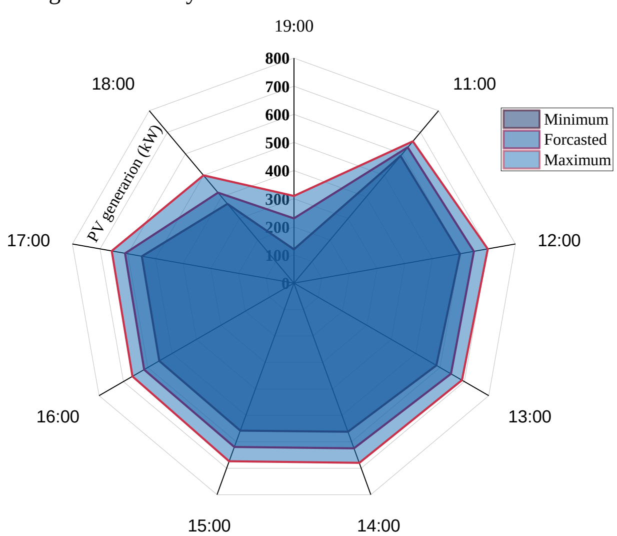

Fig. 9. The region that bounds the PV generation

Figure 10 illustrates how scheduling costs vary with an increase in the Robust control parameter, ranging from 0 to 1. The figure shows an upward trend, which supports the validity of the model and indicates that costs rise as risk aversion increases. Specifically, incorporating the worst-case scenario for forecasting errors in photovoltaic (PV) generation results in a higher net load within the service area, thereby requiring additional generation capacity to maintain peak demand at the established level.

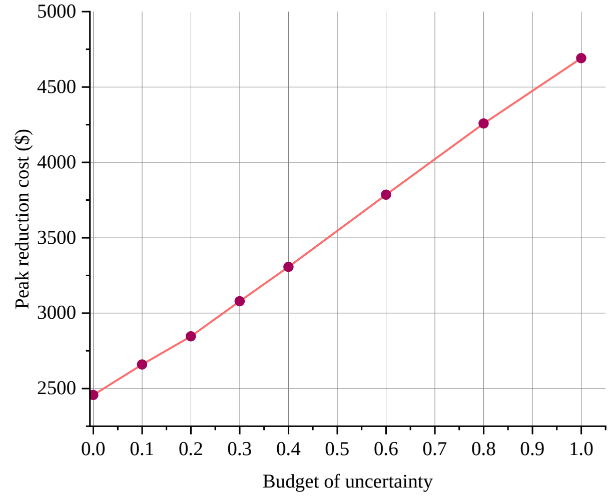

Fig. 10. Expected cost variations versus Robust control parameter

Fig. 11 represents the scheduling cost variations by increasing the robust control parameter Γ from 0-1. An ascending trend is seen in this figure that verifies the model and indicates the cost increase following the increase of the risk-averse degree. Indeed, taking the worst-case scenario of the forecasting error for the PV generation causes the increase in net load of the service area, which demands a more generation capacity to bring down the peak to the set level.

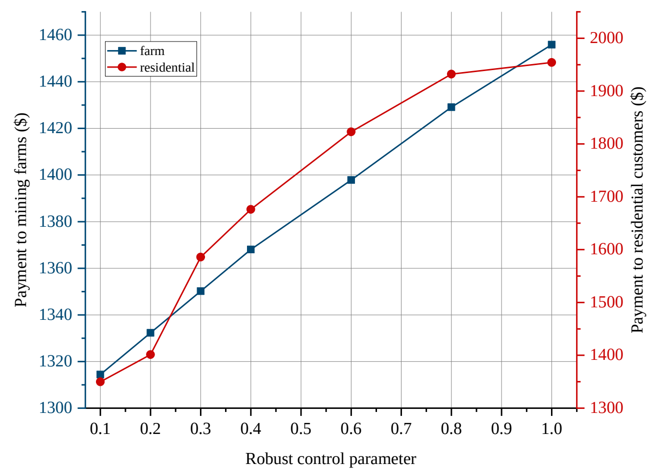

Fig. 10. Variations of expected payments to the mining farm versus robust control parameter

Variations of the incentive payments by the DisCo to the mining farms and residential with the increase of the operator's robustness are shown in Fig. 14. Similar to the scheduling cost, it is seen that the higher the robustness level, the higher the incentive payment to the customers either farm or residential participants of the ADR.

4. Conclusions

This study proposes a day-ahead scheduling framework for DRRs, integrating various programs and participation agreements to efficiently execute a peak demand reduction strategy. Beyond the conventional price-based Time-of-Use (ToU) programs designed for elastic customers, ADR programs are emerging as a critical tool, increasingly adopted by distribution system operators. The integration of IoT technologies has further enhanced the implementation of ADR by providing a seamless interface between demand response devices and the operator. The key contribution of this research is the development of an optimized scheduling approach for DRRs, aimed at minimizing peak demand within the service area of the distribution company while accounting for uncertainties in photovoltaic (PV) generation. The DRRs included in this framework encompass ToU aggregators, residential ADR participants, and mining farm ADR participants, each modeled with unique participation and power contribution characteristics.

The findings reveal that Group I DRRs play a crucial role in mitigating peak demand; however, their limited capacity is insufficient to achieve the desired reduction. Furthermore, load shifting beyond the operational period of the peak reduction scheme leads to increased energy consumption in subsequent hours. Group II DRRs are shown to effectively address power shortages at critical times, as evidenced by their maximum power contribution at 18:00, aligning with the period of minimum power generation from other DRRs and PV resources. Despite their significant impact on peak reduction, Group III DRRs are constrained by dispatch limitations and impose considerable financial costs on the distribution company, highlighting the need for careful management of these resources

The technique presented here has a significant advantage over previous approaches: it integrates the scheduling of DRRs that have different tariffs and performance contracts. The authors introduced a novel approach by considering three types of participants with distinct contracts and modeling their scheduling to effectively reduce peak load. In particular, the ToU program, a traditional price-based scheme, and the advanced ADR program, which utilizes IoT technology, provide the DisCo with greater confidence in the power contributed by these resources. This is because the implementation mechanisms for both programs minimize the need to account for customer decisions, reducing the complexity often associated with game theory. As a result, while the generated power from renewable resources may face some uncertainty in peak reduction, the power delivered by DRRs is highly reliable, thanks to the established baselines for customers and aggregators.

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