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# A NOVEL APPROACH FOR DEMAND RESPONSE ANALYSIS AND MODELLING

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## ABSTRACT
Demand response (DR) mechanisms offer a promising solution for reducing stress on distribution circuits and optimizing power system operations. With the evolution of the power sector driven by smart grid technologies, integration of distributed energy resources (DERs) and the rise in electric vehicles, DR has gained significant attention for its role in demand-side management. Significant benefits not only to consumers but also to electric utilities underscores the importance of analyzing DR from both technical and economic perspectives, as well as understanding its market structure for effective implementation and policy-making. This paper explores the DR market structure in detail, examining the interplay between wholesale and retail energy markets. It also presents a mathematical formulation for DR programs targeting aggregated loads, incorporating linear constraints with energy models to enhance flexibility DR scheduling. Using a real-time pricing scenario, the study evaluates the impact on feeder load management alongside the integration of DERs & electric vehicles. The results demonstrate significant potential for DR through load scheduling schemes, emphasizing the need for infrastructure upgrades. The study concludes that while all stakeholders can benefit from DR, success depends upon well-defined conditions for participation.

**Keywords**:
Demand Response (DR), WDRM (wholesale DR Mechanism), Distributed Energy Resources DERs), Demand side management (DSM), Electric Vehicles (EVs), DSO (Distribution system operator), TSO (Transmission system operator).

## INTRODUCTION
The importance of reliable electric power distribution systems has become increasingly pronounced with the advent of smart grid technologies, including demand-side management (DSM), the integration of renewable energy resources, and the rise of electric vehicles (EVs). These advancements are reshaping the traditional power grid, demanding new strategies to address the challenges they introduce to distribution systems. Demand-side management is crucial for enhancing the efficiency and reliability of power systems, particularly through consumer participation. DSM primarily involves two approaches: Demand Response (DR) and Energy Efficiency. According to [1], DSM programs can play a significant role in managing peak demand, reducing the need for additional generation capacity, and improving grid stability. Demand Response is the key DSM component. This paper centers on the demand response aspect of DSM, a critical tool for optimizing energy consumption and alleviating grid stress during peak hours. DR enables consumers to adjust their electricity usage in response to signals from utilities, such as price changes or incentives. As noted in [2], the implementation of DR has been increasingly facilitated by advances in digital communication and control technologies, allowing for more responsive and automated systems. DR frameworks are being adopted to cater both wholesale and retail energy markets, providing flexibility for grid operators and enhancing market efficiency. For instance, in wholesale markets, DR helps balance supply and demand, while in retail markets, it provides consumers with opportunities to reduce their energy costs through active participation [3]. Recent studies have highlighted the effectiveness of DR programs in mitigating peak loads, which can be particularly beneficial during high demand periods or when renewable energy generation is low. Incorporating demand response into energy models is a complex task, as it involves multiple variables, including the type of distribution system, the variability of energy models, and the

socio-economic behavior of consumers [4]. These models must be carefully calibrated to reflect the real-world behavior of both consumers and energy markets. The mathematical representation of DR often involves both linear and non-linear formulations. Linear models are generally favored for large-scale systems due to their simplicity and ease of integration into existing energy management frameworks. However, non-linear models may provide a more accurate representation of specific consumer behaviors and interactions within the grid. The choice between linear and non-linear formulations depends on the complexity of the system and the availability of data from utilities and consumers.

The deployment of demand response programs has been instrumental in improving grid efficiency. Research by Albadi & El-Saadany [5] reviews different DR implementations in electricity markets, highlighting their ability to reduce peak loads and improve overall system stability. Their findings suggest that while DR has significant potential, it requires a detailed understanding of market mechanisms and consumer behavior to maximize its benefits. A study by [6] explores the challenges associated with DR integration, emphasizing the need for advanced communication and sensing technologies. These technologies are essential for providing real-time data on electricity consumption, enabling utilities to offer more tailored DR programs. The study also points to the importance of regulatory support in ensuring the success of DR initiatives, particularly in deregulated markets where consumer participation is key to market efficiency. The integration of DR into modern electricity markets offers a pathway to more efficient and resilient power systems. However, achieving this requires addressing both technical and economic challenges, such as improving the scalability of DR models, ensuring data privacy, and developing incentive structures that align consumer behavior with grid needs. Researchers emphasize that future efforts should focus on enhancing the adaptability of DR frameworks to accommodate the rapid growth of renewable energy sources and the evolving demands of the energy market. Demand response represents a critical component of smart grid technology, offering a pathway to more adaptive and efficient power distribution systems. By leveraging advances in sensing, control, and communication, and by addressing the complexities of DR modeling, the energy sector can better manage peak loads and integrate renewable resources, ultimately supporting a more sustainable and reliable power grid.

**DR REVIEW & ANALYSIS**

Electric utilities aim to provide clean and uninterrupted power to customers, who in turn agree to pre-determined payment plans. For a power system to be efficient, it should maximize utility revenue while minimizing operational costs, and at the same time, reduce consumer bills while ensuring high reliability. An optimal system design requires economic analysis of demand management schemes that align with consumer behavior and needs. This is the essence of demand response (DR), where consumers adjust their energy consumption in response to price signals from utilities. Effective DR can relieve transformer overloads, reduce feeder congestion, and prevent circuit faults. DR programs can be classified based on economic approach—incentive-based and time-of-use (TOU)* programs [6-8], and based on application—industrial, commercial, and residential demand response. Industrial loads, due to their flexibility, have significant potential for DR. A study from the U.S. indicates that there is over 12 GW of DR potential in the industrial sector [9]. Commercial DR programs focus on adjusting environmental control systems to maintain comfortable conditions while minimizing energy use [10,11]. Industrial and commercial sectors are often more suitable for DR due to the presence of large, controllable loads and relatively low control costs. The Federal Energy Regulatory Commission (FERC) highlights that residential DR remains underutilized but could provide substantial reductions in peak demand. Recent research has explored various algorithms for residential DR and home energy management systems (HEM) [12-15].

A key element of successful DR implementation is the design of innovative pricing schemes. Studies on real-time pricing (RTP) and critical peak pricing (CPP) suggest that these can be effective when paired with automated load control technologies [16,19]. The role of DR in advancing smart grids has been widely discussed in recent literature [20-23], emphasizing the development of distribution system operators (DSOs), transactive energy, and pool-based demand response exchanges (DRX) to manage the variability of renewable energy sources [21]. These studies stress the importance of modeling DR within wholesale and retail markets to create a more robust revenue structure.

While many studies focus on incorporating DR into existing power systems, models for scheduling and dispatching electricity specifically within wholesale and retail demand response mechanisms (WDRM and RDRM) are still underdeveloped. The impact of DR on distribution system economics and the transition to modern electricity models requires further exploration [1,5,22,24]. A critical insight from these studies is that for demand-side management (DSM) to be economically viable, price differentials must justify the required investments in advanced communication infrastructure. A multi-objective optimization approach is explored in [23], balancing generation costs and demand reductions while considering key constraints like demand-supply balance, energy parameters, and generation capacity limits.

Further, studies such as [24] have evaluated the impact of DR on market dynamics, including the market clearing prices in both WDRM and RDRM, using unit commitment (UC) models. Simulations involving dynamic demand controllers (DDC) have demonstrated how frequency-responsive loads can be managed to enhance grid stability [25]. These methods can extend to managing the broader power network, enabling more effective DR. A.J. Roscoe et al. [26] examined the role of real-time electricity pricing in facilitating the integration of wind generation by utilizing DR during periods of low wind output. In the Korean electricity market, a reliability-based DR program was developed to offer incentives like capacity rewards and energy rewards, compensating participants for load adjustments [27]. Integration of DR algorithms into the distribution system topology has also been explored, offering better monitoring and verification of DR activities, especially within WDRM scenarios. This aligns with the growing need to define the role of DSOs in optimizing DR benefits across the distribution network.

DR can be viewed as a virtual resource exchanged between DSOs, transmission system operators (TSOs), aggregators, and consumers. Business models like bilateral and pool-based frameworks provide different approaches to managing DR transactions, with a preference towards pool-based models due to their flexibility in stakeholder participation. Recent studies [28] also highlight the use of artificial intelligence methods for optimizing DR, which could lead to the development of more effective revenue models and electricity market contracts. Other research, such as [29], has explored the techno-economic assessment of distributed energy resources (DERs) and EVs within power systems, suggesting that EVs can function as mobile storage units and provide ancillary services alongside DR. In [30], adaptive control strategies have been developed to manage frequency and voltage through demand response during grid disturbances. These advancements show that DR can not only contribute to energy management but also support stability and flexibility of power systems.

Hence, it is quite evident that DR implementation can be analyzed from diverse perspectives and its benefits are linked with better power system operation, higher customer satisfaction and cost effectiveness. The methodologies for implementing DR highlight its role in improving revenue models to promote consumer participation. As technology advances, particularly in communication and control, DR will play an increasingly vital role in shaping a more efficient and reliable energy future.

## DEMAND RESPONSE FRAMEWORK FOR ELECTRICITY MARKET

Figure below, (Fig.1.) elaborate the role of wholesale market and retail market with reference to DR. It is seen that the DR mechanism is attributed to the overlapping portion of the markets and the balancing authority deals with the overall management between the two market sources. The benefits of demand response in balancing the high penetration of renewable power like solar panels or small wind turbines is reflected in both sides of the market. The customer participation has different perspectives in the two markets. In WDRM, retailers devise electric dispatch schedule plans and contracts for end user. However, in RDRM end-user is the direct participant and they purchase DR in lieu of the changes in their power usage pattern. Demand Response Scheduling is presented in Fig.2. This involves four main participants each playing an integral role in DR management for controlling customer load either by load curtailment or through load shifting, to decrease power demand during peak hours when energy generation cost is high. The four participants are Energy balancing authority, Demand Response Aggregator, Distribution System operator/Transmission System Operator and End-user of energy. Energy balancing authority is the DR initiator and orders the total volume of demand response in accordance with the total desired volume of demand reported for particular time/duration. The aggregator gathers the demand response participant's data from the distribution system and reports the aggregated value to the balancing authority. The end-consumers willing to participate in DR programs send their consent and preferences to the aggregators. This information is also important for the supply substation of the DR participants so that the amount of DR is properly scheduled for feeders at the DR event.

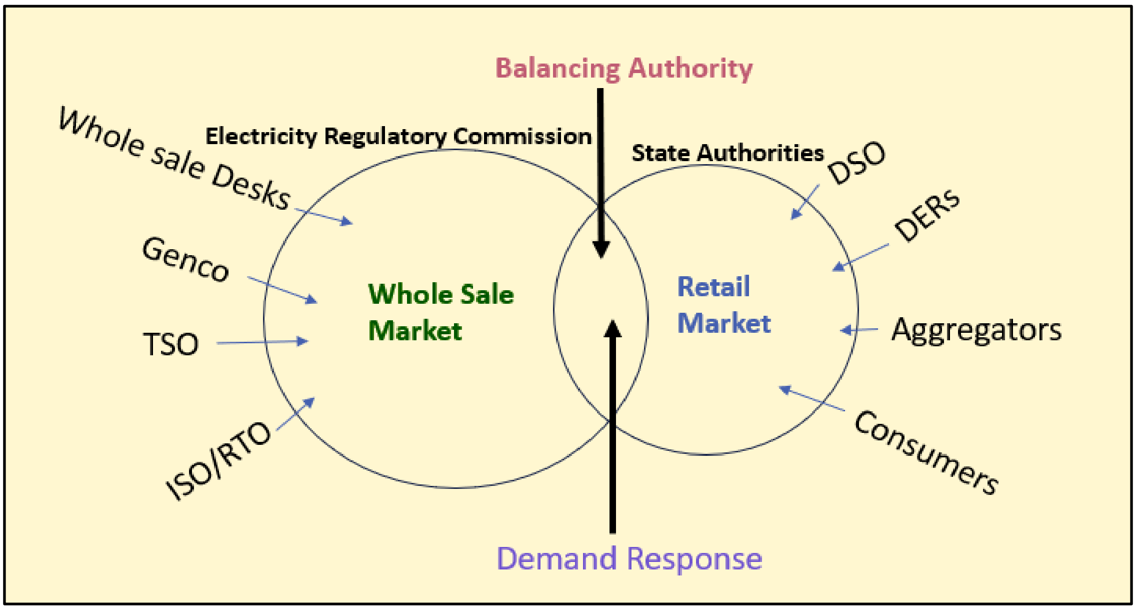


Fig. 1. DR Framework for Electricity Market.

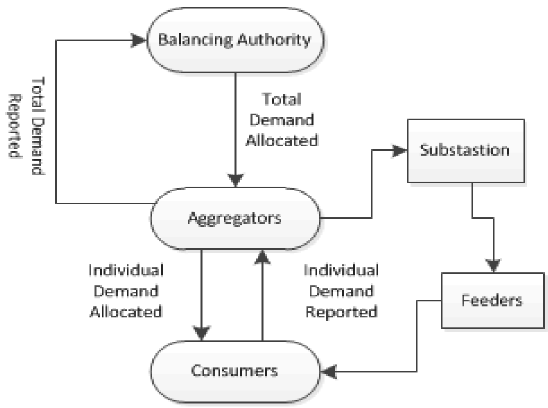


Fig. 2. Demand Response Scheduling Process

**A. DEMAND RESPONSE IN WHOLESALE MARKET**

DR framework which is applicable to whole sale market is generally termed as wholesale demand response mechanism (WDRM). In this kind of DR mechanism wholesale desks (third-party aggregators), Power Generation companies (GENCOS), Transmission system operators (TSOs) or

Independent System Operators (ISO/RTO) sell demand response. Wholesale market bidding is done to follow the dispatch plan and demand contract as settled while bidding. The aim of the WDRM is to promote demand side participation in the wholesale electricity market during high electricity prices periods or during high demand periods. This in turn may benefit the bulk power seller receiving additional payments for DR, which here is measured in MWh against the baseline estimated cost of spot price. However, in the wholesale demand response mechanism there is always a need to ramp down on short notice without attracting penalties due to the obligations associated with dispatch. Role of bidding DR into ancillary services which can only be dealt with in whole sale electricity market is another important aspect. Prior to deregulation, ancillary services were provided by the generators, however, the integration of intermittent generation and the development of smart grid technologies have initiated a shift over these resources in the system to provide ancillary services.

**B. DEMAND RESPONSE IN RETAIL MARKET**

Demand response participants for RDRM are DSOs (Distribution System operators), DERs (Distributed energy resources), Aggregators. Aggregators interact with balancing authorities and provide DR schedules to the consumers. The DR applicable to retail market is generally of two types. One is price-based DR and another is reliability-based DR. Here the purpose is solely to reduce peak-load consumption and increase off-peak demand. Incentive-based models are proposed to maximize retailer benefits by influencing customer behaviours. Most of the previous research work reported on DR, focus the retail market mechanism. The architectural needs of the DR especially for promoting end-consumer participation are addressed in research works for RDRM. The market is divided into three sectors i.e., residential sector, industrial sector and commercial sector. The objective is to maximize the utility benefits without compromising on consumer comfort levels subject to minimization of daily energy consumption levels. The outcome of the factors like time of use (TOU) prices, incentive rates and demand elasticities on shaping the load curve have been researched upon extensively to understand the process of DR.

**DEMAND RESPONSE MODELLING FOR AGGREGATED LOADS**

DR through load shifting can be achieved by deferral of non-critical loads. It is characterized by the ability of certain loads to delay or anticipate consumption during given time span. Loads used for space heating/cooling or refrigeration can be utilized here due to their heat/cold storage feature. Certain other loads like geysers, water pump or electric vehicles can be made to run in deferral mode because of their storage feature and rest of the loads operate with demand flexibility feature for not being critical or emergent loads. Not only usage pattern affects the load shifting for DR but also the technical constraints of load play important role. Hence these are always incorporated in the DR models. Demand response with respect to load shifting becomes more meaningful when dynamic pricing effect is also taken into consideration and hence overall formulation becomes more effective and beneficial for both the utility as well as the consumers wherein utility is released from undue stresses and consumers saves on monthly bills without compromising much on demand and comfort levels. Here DR model for load shifting with aggregated load and electric vehicle integration is presented. The total consumption $P_t^{DR}$, Cost $C_t^{DR}$ & time delay $d_t^{DR}$ can be expressed as

$$\left.\begin{aligned} P_t^{DR} &= P_t^0 + P_t^+ - P_t^- \\ C_t^{DR} &= C_t^0 + C_t^+ - C_t^- \\ d_t^{DR} &= D_t^0 + d_t^+ - d_t^- \qquad \forall t \end{aligned}\right\} \qquad (1)$$

The optimization problems are formulated as:

$$\text{Maximize } \sum_{t=1}^{T} P_t^{DR} \qquad (2)$$

Minimize $\sum_{t=1}^{T} C_t^{DR}$ (3)

Minimize $\sum_{t=1}^{T} d_t^{DR}$ (4)

Where, $\sum_{t=1}^{T} P_t^{+} = \sum_{t=1}^{T} P_t^{-}$ (5)

$$\left.\begin{array}{l} d_t^{-} \leq d_t^{+} \leq D_t^{0} \\ P_t^{+} + P_t^{0} \leq P_t \\ P_t^{-} \leq P_t \leq + P_t^{0} \\ C_t \leq C^{0} \leq C_{max} \end{array}\right\} \quad (6)$$

$$P_t^{DR}, P_t^{+}, P_t^{-} \geq 0 \qquad \forall t$$

Here, $P_t^0$ is the base demand and $P_t^+$, $P_t^-$ are increment / reduction of demand for total number of T time periods in the complete time span defined for DR. $P_t$ is the predefined maximum demand. $C_t$ is the cost of energy in time interval t, $C^0$ is the maximum cost agreed upon by the consumer and $C_{max}$ is the maximum cost of energy defined by utility. $d_t^-$ , $d_t^+$ are the allowed time delays/advancement for power up & down & $D_t^0$ is the maximum time span for which DR is carried over. (6) defines the constraints involved. A free variable $E_t$ can be incorporated here to represent storage level of inhouse power generation like Photovoltaic solar generation. New constraint, $E_0$ comes to track the State of charge, SOC and for minimum and maximum storage capacities, $E_0$, $E_{min}$ and $E_{max}$ respectively.

$E_t = E_{t-1} + P_t^{+} + P_t$ (7)

$E_{min} \leq E_t \leq E_{max}$ (8)

$E_0 = E_t \leq E_{max} \qquad \forall t$ (9)

Electric vehicle charging and discharging create a great impact on DR models and show considerable potential. The total EV energy inventory can be modelled as follows.

$E_t = E_{t-1} + P_t^{G2V} * \eta^{G2V} - (P_t^{V2G} / \eta^{V2G}) - E_t^{drive}$ (10)

$E_{min}N^{Plugged} \leq E_t \leq E_{max}N^{plugged}$ (11)

$0 \leq P_t^{G2V} \leq P_{tmax}^{G2V} N^{Plugged}$ (12)

$0 \leq P_t^{V2G} \leq P_{tmax}^{V2G} N^{Plugged} \qquad \forall t$ (13)

$P_t^{G2V}$ and $P_t^{V2G}$ are the power consumed and deliverd by the EV respectively. $\eta^{G2V}$ and $\eta^{V2G}$ are the respective efficiencies for vehicle to grid (discharging) and grid to vehicle (charging) operations. $E_t^{drive}$ is the total electric consumption of all the EVs while driving. $N^{Plugged}$ is the total number of EVs connected to the system and $E_{max}$ and $E_{min}$ are the maximum and minimum energy storage capacity per vehicle. $P_{tmax}^{G2V}$ and $P_{tmax}^{V2G}$ are maximum charging and discharging capacities of an EV.

## RESULTS AND DISCUSSION

The mathematical formulation results, depicted in the figures below illustrate the impact of a demand response (DR) program on an integrated power system. The solid yellow line shows the demand profile, while the purple line represents the pricing scheme in Rs/MWh. The dashed line indicates the DR program outcome, with Pt+ and Pt- shown in blue and grey columns, respectively. Four different scenarios were analyzed and the outcome is presented below (fig.3-5).

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Scenario 1: Here the outcome is based on (2) & (3) where the idea is to minimize the electricity cost while excluding customer preferences. This is the case for aggregated modelling for WDRM. It is a kind of valley filling DR program. It is seen that the total cost is here is reduced to 30%. The demand of 10MW is reduced for the 1st & 2nd time span and in turn the same amount is recovered during low price period in the time span 8 & 9.
Scenario 2: This involves DR implementation based on consumer-defined constraints and interaction with utility-defined pricing. Many a times customer preference is minimum delays/advancement in time for load shift hence the delay/advancement has to be minimized while running DR. The outcome includes (4). Fig.4. elaborate this scenario where load curtailment of around 10MW is shifted to the nearest best possible time span i.e., from span 2 to span 3. Also, the load of around 8-10 MW is increased in low price time span 9. Here the load shifting time advancement is done for more effective results. The overall cost reduction is 22% but here the customer preferences are included.
Scenario 3: In this case, demand shifting occurs during time spans 2 and 8. A high-demand period (35 MW in span 2) shifts by one time span, while a low-demand period (18 MW in span 9) spreads over spans 8 and 9. Time delay/advancement constraint is again included here. Overall electricity cost is reduced by 23%.

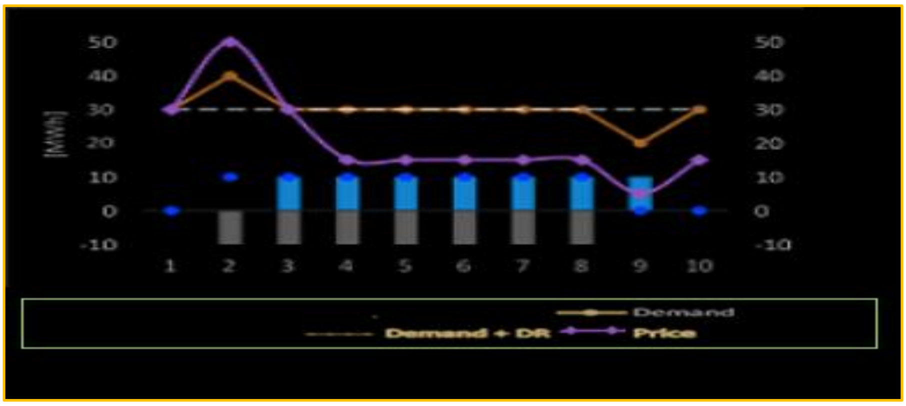


Fig.3.Scenario1: DR Without Customer Preferences

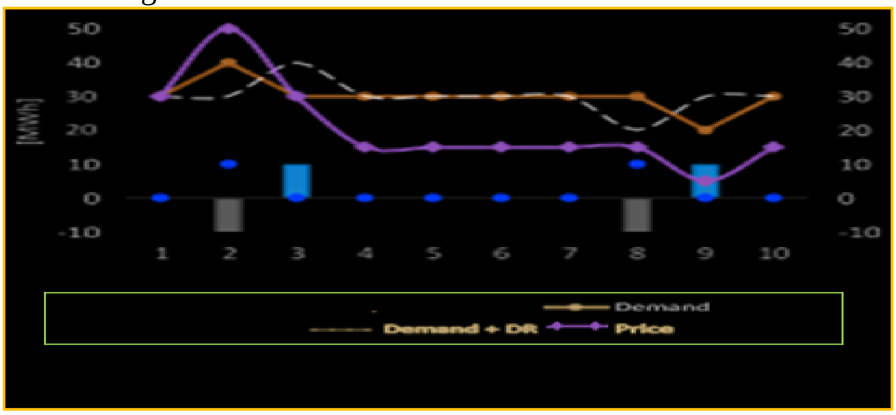


Fig.4. Scenario2: DR With Customer Preferences

Scenario 4: This scenario integrates distributed energy resources (DERs) and electric vehicles (EVs) into the DR program, further improving cost efficiency. With DER and EV integration, the total energy cost reduction increases to 38%. Load shifting is minimal due to the rapid recovery capability of these additional energy sources. It can be seen that in high price span 2 & 3 there is around 8-10 MW demand reduction/addition in high/low price time spans 2,3 & 8,9 respectively.

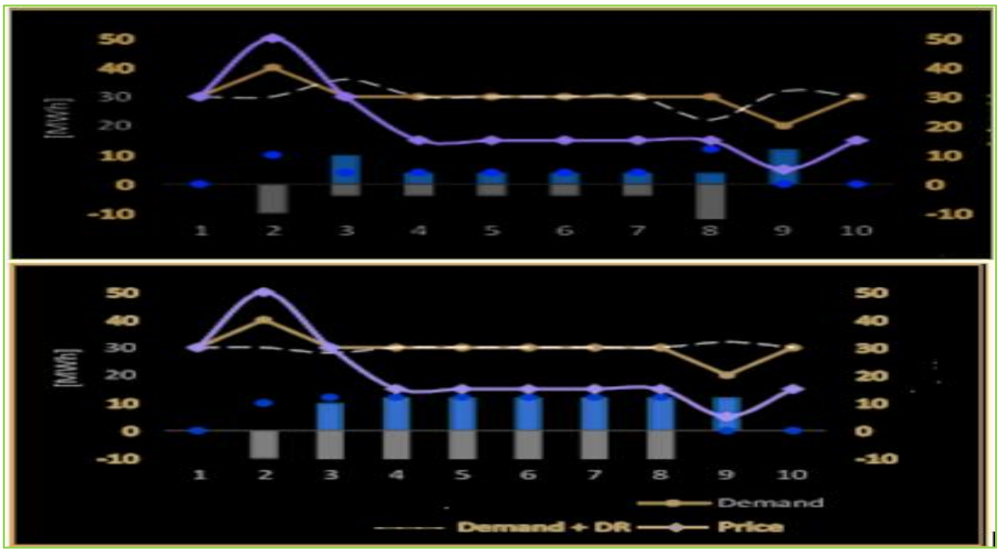


Fig.5. Comparison: Scenario 3 (DR With Customer Preferences) & Scenario 4 (DR With Customer Preferences & Ders & Evs Integration)

## CONCLUSION

In the first part of the paper effort has been made to provide insight into electrical energy market while discussing market organization and functioning. The paper is unique in the sense that this kind of literature review and analysis which is focused on the electrical energy market is not done before. The importance of this part of study lies in the effective designing and implementation of energy contracts. Study also gives an idea of the type of DR program which may be devised with respect to the energy market i.e., WDRM or RDRM. The second part of the paper presents modelling DR for aggregated loads. This study could be useful for devising sector wise (residential, commercial, industrial) demand response programs. The formulation presented can be easily extended to include more elaborated and specified customer preferences because demand response is meaningless if customer satisfaction is not considered while devising DR scheduling.

The linear nature of the mathematical formulation simplifies computation, making the DR program practical for implementation. The study provides insights into DR's potential for cost reduction and demand management in modern, smart-grid environments. Future research will explore power flow analysis with DR across wholesale and retail markets for even more effective scheduling programs.

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