Robust Multi-Objective Optimization for the Iranian Electricity Market Considering Green Hydrogen and Analyzing the Performance of Different Demand Response Programs

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Abstract

Using renewable energy sources (RES) and green hydrogen has increased dramatically as one of the best solutions to global environmental issues. Applying demand response programs (DRPs) in this context could enhance the system's efficiency. Evaluating different DRPs' performances and assessing economic impacts on different parts of the electricity market is essential. The inherent uncertainty of RES and prices is inevitable in electricity markets. As a result of the lack of information, it is crucial to mitigate the risks as much as possible, such as risks related to changes in demand, unit outages, or other traders' bid strategies. This research introduces a robust multi-objective optimization method to reach the most confident plan for the retailer based on uncertainty in RES and price. The integration of different DRPs is assessed according to the cost to retailers and benefits for consumers using a multi-objective model to survey the impacts of different parts' decisions on each other.

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The trade-off among DRPs is considered in this model, and they are traded using a new model to illustrate the daily effect of these programsin monthly operation. This paper uses hydrogen storage (HS) integrated with PV as a distributed energy resource. As the Iranian electricity market has just been established, this research proposes a framework for decision-making in new electricity markets to join future smart energy systems. The mid-term pricing evaluates the system's performance for more accurate monthly results. Also, the operation cost of the hydrogen storage is modeled to assess its performance in non-robust and robust scheduling. Mixed-integer linear programming (MILP) has been used to model this problem in GAMS. A developed linearizing method is considered with a controllable amount of errors to reduce the volume and time of the computation. Finally, the cost of consumers in non-robust and robust market planning in the presence of DRPs is reduced by 8.77% and 9.66%, respectively, and HS has a compelling performance in peak-shaving and load-shifting.

Keywords: Robust Optimization, Electricity Market, Green Hydrogen, Demand Response, PV.

Nomenclature

Acronyms

CAES	Compressed air energy storage
CC	Consumers' costs
CHP	Combined heat and power
CSP	Concentrated solar power
CVaR	Conditional value-at-risk
DER	Distributed energy resources
DLC	Direct load control
DR	Demand response
DRP	Demand response program
EH	Energy hub
ESS	Energy storage system

EV	Electric vehicle
FC	Fuel cell
GAMS	General algebraic modeling system
GHG	Greenhouse gas
HS	Hydrogen storage
IDR	Integrated DR
IGDT	Information gap decision theory
MILP	Mixed-integer linear programming
NLP	Non-linear problem
OPF	Optimal power flow
P2H	Power-to-heat
P2H2	Power-to-hydrogen
PDF	Probability distribution function
PO	Pool-order DR
PV	Photovoltaic
RB	Reward-based DR
RC	Retailer's cost
RES	Renewable energy sources
RL	Reinforcement learning
RO	Robust optimization
RTP	Real-time price-based
SES	Smart energy system
WT	Wind turbines

Indices

poo	Pool-order DR index
t	Time-period: hour
d	Time-period: day
m	Time-period: month
i	The segment index in Reward-based DR

Numbers

N_m	The number of the months
N_{poo}	The number of the Pool-order DR contracts
N_d	The number of the days
N_i	The number of segments in the Reward-based DR

Parameters

$W_{poo}(m)$	Energy price in Pool-order DR
$P_{poo}^{Max}(m)$	The maximum demand in the option contract
$\bar{P}_i^{rb}(m)$	The demand in step i in Reward-based DR
$\bar{R}_i^{rb}(m)$	The maximum reward in step i in Reward-based DR
C_{rtp}	Percentage of shiftable load in RTP DR
$Load_{m,d,t}$	Hourly demand for each day of each month
$P_{m,d,t}^{pv}$	Generated power by PV power plant
$P_{m,d,t}^{Min,el}$	The minimum power for electrolyzer activation
$P_{m,d,t}^{Min,fc}$	The minimum generated power by FC
$P_{m,d,t}^{Max,fc}$	The maximum generated power by FC
η_{fc}, η_{el}	The electrolyzer and fuel cell efficiency
$P_{m,d,t}^{Min,s}$	The minimum hydrogen levels for hydrogen storage
$P_{m,d,t}^{Max,s}$	The maximum hydrogen levels for hydrogen storage
b^{el}, c^{el}	The electrolyzer cost function factors
a^{fc}, b^{fc}, c^{fc}	The fuel cell cost function factors

Decision variables

$p_{poo}(m)$	The monthly purchased energy from the Pool-order DR
$Pen_{poo}(m)$	The not executing penalty of the option
$P_{poo}^{total}(m)$	The total purchased demand from Pool-order DR
$P_{m,d,t}^{h,poo}$	The hourly purchased power from the option
$Re_i(m)$	The value of reward in step i in Reward-based DR
$R^{rb}(m)$	The value of the reward each month in Reward-based DR
$P^{rb}(m)$	The monthly demand participated in the Reward-based DR
$P_{m,d,t}^{h,rb}$	The hourly participation in the Reward-based DR
$RTP_{m,d,t}$	The shifted demand in RTP

$P^{el}_{m,d,t}$	The consumed power by the electrolyzer
$P^{fc}_{m,d,t}$	The generated power by the fuel cell
$P^{s}_{m,d,t}$	The level of the stored hydrogen in the storage
$F^{el}_{s}\left(P^{el}_{m,d,t}\right)$	The electrolyzer cost function
$F^{fc}_{s}\left(P^{fc}_{m,d,t}\right)$	The fuel cell cost function
$U_{poo}\left(m\right)$	The binary variable that shows the option contract activation status
$U^{rb}_{i}\left(m\right)$	The binary variable that shows the segment activation in Reward-based DR
$U^{el}_{m,d,t}$	The binary variable that shows the electrolyzer status
$U^{fc}_{m,d,t}$	The binary variable that shows the fuel cell status

1. Introduction

1.1. Motivation

Currently, energy management has become a global challenge with rapidly increasing demand and declining non-renewable resources. In fact, smart energy systems (SESs) have been introduced as one of the solutions to global energy challenges [1] . Therefore, a sustainable energy supply is vital for present and future societies because of the growing population and the different needs of future generations. According to recent studies, a mix of long and short-term scheduling has become necessary for SESs [2, 3].

The energy market's importance has increased with the smart grid energy management development. This market was initially attractive to electricity sellers and retailers; the consumers took more attention over time, and all players sought to optimize their objectives [4]. The energy market has also optimized consumption, raised public awareness about energy management, and reduced costs. However, the direct exchange of electricity is a commodity in this market, as in other financial markets.

Demand response programs (DRPs) became popular in solving energy system problems due to the high energy cost and rapid population growth. In fact, demand response (DR) is generally divided into two sections: incentive-based and price-based [5, 6]. Peak-shaving, load-shifting, smoothing the load curve, and reducing the retailer risk are the essential benefits of DRPs. In addition, the demand flexibility of small consumers can increase system reliability, and they will become more important with the expansion of smart grids. Dynamic pricing approaches are widely expected to increase the effectiveness of small consumers. Accordingly, integrating DRPs and renewable energy sources (RES) significantly increases the utilization of small sources such as photovoltaic (PV) and wind turbines (WT) [3].

The uncertainty has a significant impact on decision makings. In fact, uncertainties should be taken to achieve optimal energy management strategies and readiness for future demand. The complexity of SESs and different market strategies have resulted in uncertainty. It is also considered for problem data such as RES generation, market price, and electrical and thermal demand [7]. Different approaches are used to model uncertainty, such as stochastic, robust, and information gap decision theory (IGDT). The main characteristic of robust optimization (RO) is considering the worst variable conditions for risk-averse optimization, and the computational time is considerably low because of the linear modeling.

RES have been considered in the energy portfolios of many countries due to the lack of availability of fossil fuels, pollution, and transmission and maintenance problems. Furthermore, the research shows that RES have reached the level of competition with conventional energy systems in terms of techno-economic-environmental-social perspectives [2, 8, 9]. Moreover, RES could help communities reduce climate change's effects, and numerous countries are searching for ways to achieve a zero-emission energy system by 2050. Further, RES have a compelling performance in energy security and energy mix.

On the other hand, the energy storage system (ESS) is also a reliable solution due to the fluctuating nature of RES and a sustainable energy system. An off-grid energy system can be operated in remote areas [10]. In recent years, hydrogen has been part of developed countries' plans for the coming years due to its application in various sectors such as electricity, industry, and transportation. In addition, hydrogen-based energy technologies have shown that hydrogen can be used as a zero-emission fuel to generate electricity. There are several ways to produce hydrogen, such as green hydrogen could receive its energy from RES. However, peak-shaving is essential due to the increased energy demand and peak hours. Although the total peak hours in Iran are about 200 hours per year, solving this challenge is crucial [11]. Therefore, in addition to peak-shaving and load-shifting, hydrogen storage (HS) will play an essential role in the future world economy [12].

1.2. Literature review

The effectiveness of DRPs in the energy management sector is not avoidable. DRPs, mainly focused on the energy sector's residential part, are spreading worldwide to maximize the benefit of managing the demand. In this regard, many studies have focused on utilizing DRPs in electricity markets. These programs' classifications help managers enhance their behavior and maximize their performance in the electricity market. Literature [13] introduced definitions and classifications of DRPs from a comprehensive point of view, and according to this research, DRPs are generally divided into incentive and price-based categories. In the price-based class of DRPs, Pourmousavi et al. [14] introduced real-time pricing in energy management. Also, Celebi and Fuller [15] proposed time-of-use (TOU) pricing. It could enhance consumer behavior under different strategies. Implementing price-based DRPs has improved the effectiveness of pricing methods. In [16], a simple incentive pricing was proposed based on a game-theoretic scheduling approach for smart grids. The results have proved that it could alleviate the peak-to-average ratio in the system. Marzband et al. [10] combined day-ahead and real-time scheduling to obtain the best price and optimal usage of distributed energy resources (DER). In this literature, the simulation results have defined an 8.5% reduction in power generation cost. The impact of uncertainty was not considered in these works, which could hugely affect the performance of the DRPs in the system, and they were mainly focused on introducing the program. Lu et al. [4] studied a multi-objective problem considering the performance of dynamic pricing DR by reinforcement learning (RL). In addition, the researchers attempted to take the initiative and use a combination of different DRPs. In [12], TOU and RTP DRPs were combined. In this research, the uncertainty was considered for electricity and hydrogen vehicle demand, and it was introduced in the concept of the energy sector. In this research, outcomes showed that hydrogen fueling stations could reduce costs by 9.6%. In addition, integrated DR (IDR) was introduced in energy hubs (EHs) for optimal planning of the integrated electricity and gas systems [17]. Moreover, in the incentive-based DRPs, some programs are introduced, which are evaluated weekly or monthly to provide the consumers with the profits of reducing their demand at the end of the time zone. A reward-based DR was announced in [18] to minimize the operation cost. This research considered the uncertainty for market price and consumer behavior in a stochastic approach. Further, the concept of pool-order DR was defined by Nguyen et al. [19]. Also, the importance of the consumers' role in DRPs modeling is vital to be considered. The research [20] has reviewed market demand-side strategies to analyze consumers' roles. In another study [21], Mahmoudi et al. analyzed long-term planning for retailer's cost minimization based on four DRPs: reward-based, pool-order, spike-order, and forward DR. In this work the uncertainty of electricity market price was considered using the stochastic method. Another uncertain parameter was consumers' collaboration in those DRPs to evaluate the impact of the consumers' behavior involved in uncertainty. According to the results, collaboration in summer was higher than in winter. In [6], three DRPs were considered to minimize the operation cost using a robust approach based on risk-neutral and risk-averse strategies to obtain robustness against uncertainty and tackle possible risks. This research was done in the mid-term time domain. The main structure of the study mentioned above is to evaluate the mid-term and short-term DRPs separately. The combination of different DRPs introduced in the mid-term and short-term needs to be assessed to allow the consumers to manage their participation based on their welfare and obtain hourly behavior to manage energy production and evaluate their performance. These points were not considered in these studies. The trade-off among these DRPs is vital to help retailers manage their behavior in the electricity market. Also, it is crucial to consider the retailers' and consumers' behavior simultaneously; so that the urge for multi-objective optimization is apparent. Also, the need for robustness against uncertainty and risk is inevitable if a market is to launch or a new DRP is applied to a market structure to calculate the possible strategies in worst-case scenarios.

Nowadays, DRPs have enormously enhanced the energy sector's performance. Much research has been done in this sector, and various viewpoints have been evaluated. In addition, the objective functions concern different parts of the energy systems, such as regulators, retailers, or the owner of the components. In [22], a robust-stochastic approach was applied to maximize the profit of a concentrated solar power (CSP) plant. [23], has considered conditional value-at-risk (CVaR)-based stochastic uncertainty modeling. These two research optimized the owner of the power plant's performance in the presence of uncertainty. [24], minimizes the generation cost and emission considering optimal power flow (OPF) and unit commitment problems (OPF-UC). The proposed scenario reduced the objectives by 10.5%. Zeynali et al. [1] proposed a hybrid robust-stochastic method to achieve a cost-emission reduction goal. The findings defined that a 4.4% and 40% reduction in cost and emission were reached, respectively. Recently, different cooling and heating technologies were compared to find the optimal operation of EHs [25]. The objective functions of these papers concern the regulator to optimize their performance in the energy sector. Study [7] analyzed the impact of thermal and electrical uncertainty with stochastic modeling. In this paper, a 2% and 6% increase in profit and electricity market price were obtained due to the use of the compressed air energy storage (CAES) system. In the literature, case 4 decreased the operation cost by 4.3% compared to case 1. A scenario-based method applied uncertainty to zonal electricity prices to reduce the risk to retailers [26]. [27], analyzed the performance of multi-energy microgrids in sustainability and flexibility contexts. In these papers, the writers evaluated the retailers' performance in the concept of the electricity market, and the uncertainty was considered to obtain a reliable result. The lack of assessing the performance of the electricity market's participants using a multi-objective optimization is evident in these works. Also, the effectiveness of DRPs is not considered, which could hugely affect their performance. On the other hand, much research has been conducted to obtain the stakeholders' performance in the presence of DRPs. In [28], four cases were proposed to optimize parking lots' energy management considering PV, WT, and HS. Firouzmakan et al. [3] used direct load control (DLC) programs to minimize electricity and thermal grid operation costs. The uncertainty parameters, such as RES output, electrical load, and electricity price, were considered. In [29], electric vehicles (EVs) were used as storage in industrial zones to reduce operation costs and maximize RES penetration. This paper considered stochastic modeling for PV, WT, geothermal PP, and EVs behavior (arrival, departure, and distance). Results showed that the relative operating cost has decreased by 15.7%. In addition, in [5], different power-to-x technologies, such as power-to-heat (P2H), power-to-hydrogen (P2H2), and combined heat and power (CHP) units, were considered to optimize the daily operating costs. Considering IDR with stochastic-robust modeling could decrease the operation cost by 15% [30]. WT and PV generation was modeled by a stochastic approach, while RO modeled the market price. In [31], multi-objective IGDT optimization was introduced for multi-energy microgrids considering hydrogen refueling stations and EV parking lots to reduce retailer costs. The simulation results declined the objective function by 76.35%. [32], focused on thermal, natural gas, and electrical demand uncertainties with a hybrid robust-stochastic approach. These papers were conducted in the short-term time domain considering the energy production sector, and the DRPs introduced in the mid-term or long-term were not considered. Also, the uncertainty was modeled on various data using the stochastic method, which could severely increase the computational volume. Furthermore, Aghamohammadloo et al. [33] surveyed multi-objective planning for the retailer and consumers. IDR was applied in a game theory environment with uncertainties. In another research [34], a game theory-based DRP combined incentive and price-based DRPs for dynamic pricing were introduced, and the simulation results proved that the utility profit increased by 16.06%. In these papers, the lack of considering the trade-offs among different DRPs is evident. Also, the RO method that is needed to obtain a reliable result and robustness against risk and uncertainty, especially at the beginning of the operation of a newly established structure, is not evaluated. Further, some studies focused on environmental and social goals [2, 8, 35], and a summary of recent research is shown in Table 1. Previous characteristics are described with six criteria to show their relevance and weaknesses.

Table 1: A summary literature review

Ref.	DRPs	Uncertain par.	Modeling	Beneficiary	Solution method	Scope
[14]	RTP	–	–	–	PSO algorithm in MATLAB	Short-term
[16]	A simple incentive pricing	–	–	Consumer	Game theory	Short-term
[19]	Pool-prder DR	–	–	Regulator	MINOS-GAMS	–
[22]	–	CSP generation Pool market price	Robust Stochastic	Power plant owner	CPLEX- GAMS	Short-term
[15]	TOU	–	–	Regulator	PATH- GAMS	Short-term
[10]	DAP-RTP	–	–	Retailer	–	Long-term
[18]	Reward-based DR	Pool market price Consumer behavior	Stochastic	Retailer	CPLEX-GAMS	Short-term
[36]	RTP	–	–	Retailer	MGSA algorithm in MATLAB	Short-term
[21]	Reward-based DR Forward DR Pool-order DRS pike-order option	Pool market price Consumer participation	Stochastic	Retailer	CPLEX-GAMS	Long-term
[28]	TOU	–	–	Regulator	CPLEX- GAMS	Short-term
[26]	–	Zonal price	Stochastic	Retailer	MOSEK- GAMS	Mid-term
[4]	Dynamic pricing	Demand	AI-RL	Retailer Consumer	Java-Eclipse	Short-term
[37]	TOU	WT generation	Stochastic	Retailer	DICOPT- GAMS	Short-term
[6]	Pool-order DR Forward DR Reward-based DR	Pool market price	Robust	Retailer	CPLEX-GAMS	Mid-term
[3]	DLC	PV generation WT generation Market price Demand	Stochastic	Retailer	MOPSO algorithm	Short-term
[24]	–	WT generation	Stochastic	Regulator	XPRESS- GAMS MATLAB	Long-term
[17]	Integrated DR	–	–	Regulator	MATLAB	Long-term
[29]	TOU	PV generation WT generation Geo. PP generation EVs behavior	Stochastic	Regulator	BARRON-GAMS MATLAB	Short-term
[1]	–	WT generation EVs behavior	Robust Stochastic	Regulator Consumer	CPLEX- GAMS	–
[5]	TOU	Market price	Robust	Retailer	SBB- GAMS	Short-term

[7]	–	PV generation CSP generation Electrical demand Thermal demand	Stochastic	Retailer	CPLEX- GAMS	Short-term
[30]	Integrated DR	PV generation WT generation Energy market price	Stochastic Robust	Retailer	DICOPT- GAMS	Short-term
[31]	Heat and power DRPs	PV generation WT generation	IGDT	Retailer	CPLEX- GAMS	Short-term
[27]	–	PV generation WT generation Demand Market price	Stochastic	Regulator	IPOPT- MATLAB	Short-term
[12]	TOU RTP	RTP WT generation Demand Hydrogen vehicles demand	Risk-constrained stochastic	Retailer	CPLEX	Short-term
[33]	Integrated DR	–	–	Retailer Consumer	Game theory	Long-term
[23]	–	Market price WT generation CSP generation	CVaR-based Stochastic-Interval	Power plant owner	CPLEX- GAMS	Short-term
[32]	TOU	WT generation Thermal demand NG demand Electrical demand	Robust Stochastic	Regulator Consumer	CPLEX- GAMS	Short-term
[38]	RTP	–	–	Regulator	GA algorithm in MATLAB	Mid-term
[25]	–	PV generation WT generation	Stochastic	Regulator	GA algorithm in MATLAB	Short-term
This research	RTP Pool-order DR Reward-based DR	Pool market price PV generation	Robust	Retailer Consumer	CPLEX- GAMS MATLAB	Mid-term

1.3. Research gap and contributions

The necessity of having a comprehensive pricing plan in the electricity market to optimize the consumers' and retailers' costs and evaluate the impact of different DRPs, prompted this study to explore this topic. A model with low computational volume should be used for this approach, so linear programming as a widely used method for optimization and modeling is considered. The retailer participates as an investor in the energy production sector in the market and, in this way, could be regarded as the owner of a generation unit. Thus, three main parts of the electricity market have collaborated in this modeling. Also, the evaluation needs to be done to obtain the result of DRPs' impact, whether they are defined in the mid-term or affect the short-term behavior. Due to this reason, a new modeling of DRPs is proposed to show how DRPs defined in the mid-term should be managed during the day. Moreover, the impact of consumers' behavior on the retailers' decision-making process is inevitable. Retailers affect the consumers' behavior using the price. Thus, multi-objective optimization is necessary when market behavior is the research subject.

Climate change mitigation requires global cooperation, and many conventional energy systems cannot participate. Although these systems have not yet reached the level of smart systems, recent research has focused on developed and modern energy systems. This research aims to use the significant potential of these emerging markets for climate mitigation. By using this decision-making tool, the retailer can gain investors' trust. On the other hand, investors can analyze the results of applying different conditions for their goals. DRPs, as influential possibilities in the electricity market, are the main structure between the retailer and consumers that hugely affect different parts of the system's behavior. This reason makes it vital to consider the trade-off among different programs. Due to this necessity, DRPs defined in the mid-term are brought to the daily time zone using our new modeling to mix DRPs from different time domains and survey their impact on decision-making. In addition, the effect of uncertainty in market price and PV production on the market behavior and the retailer decision-making process is inevitable. In much research, the stochastic optimization approach modeled the uncertainty with a large computation volume. The RO using the linearization model is more suitable for optimization, where the RO method could create a high confidence level for the decision-maker because of its conservativeness. This approach becomes crucial when a newly launched market structure is the case study.

According to the impact of DRPs on the market, a mid-term analysis of this impact is crucial. Consumer welfare and DRPs' performance determine how retailers should optimize their costs. This research model could help retailers manage their budgets and achieve more profit or advertise based on socio-economic goals to encourage consumers to choose the DRP with the best outcome for the retailer considering direct trade between market players. There is uncertainty involved in the decision-making process of the retailer to decide which DRP is more profitable. Therefore, the impact of the uncertainty could also be evaluated. Retailers are investing in this market because RESs provide an opportunity to increase their economic status. In addition, integrating these technologies with ESSs increases profits. the other hand, green hydrogen will be a vital part of future SESs due to the development of hydrogen worldwide. Moreover, the inherent uncertainty of RES widely affects the performance of ESSs in the system. Thus, it is crucial to consider the uncertainty to achieve a valid point of view on their behavior. The retailer's price charges from the consumers are also an influential factor influencing the ESSs performance. Further, the ESS could affect the retailer's decisions in applying the DRPs. Therefore, it is necessary to model an optimum decision-making process for the scheduling of the ESS. The novel contributions of the proposed methods are as follows:

- **RC1**:Considering the trade-off between different DRPs.
- **RC2**:An improved upper approximation method for the fuel cell cost function, in which the number of segments is determined based on an acceptable error suggested by the operator
- **RC3**:Using robust multi-objective programming to survey the socio-economic aspects of the electricity market.11
- **RC4**:Mid-term evaluation for operational planning of different market components
- **RC5**:Mid-term scheduling for ESS considering uncertainty using the RO method
- **RC6**:Assessing the daily operation of mid-term DRPs founded on the retailer and consumers' cost.

1.4. Paper organization

The rest of the paper is categorized as follows: Section 2 describes the proposed plan of this research. Methodology, formulation, and constraints are defined in Section 3. Moreover, section 4 discusses case studies and simulation results in-depth, and at the end, the conclusion and future suggestions are presented in Section 5.

2. Proposed plan

Figure 1 shows an illustration of the proposed market. In this market, the trade-off between retailers and consumers has been analyzed with three DRPs (PO, RB, and RTP). HS integrated with a PV system is proposed for the market. Whenever the green HS costs are more profitable than the pool price, the retailer could supply the market as a power plant owner. The multi-objective function of this study minimizes retailer and consumer costs simultaneously with a robust approach. cording to the newly established electricity market in Iran, where consumer behavior and participation in DRPs could not be predicted, the necessity of evaluating and forecasting DRPs implementation in this system is inevitable. Further, uncertainty is one of the main aspects of the system in a newly established electricity market. The advertisements and various encouragements should be taken into account to use the benefits of the market features. Moreover, the retailers have a clear rule in this structure, and a proper plan to participate in an economical and beneficial activity in the market structure is vital. Furthermore, the evaluation is done to discover the retailer and consumer economic advantages and provide a valid point of view to guarantee their benefits. Consequently, RO is considered to obtain a reliable decision-making plan and counter different sources of risk. Therefore, pool-order DR, reward-based DR, and RTP programs are applied to fulfill the goals. addition, policies in Iran for implementing RES and integrating these components with the electricity market are considered in this research. On the other hand, the integration of ESS with RES and their performance in the electricity market encouraged the writers to consider ESS. Further, modeling and simulations are done for a mid-term period to validate the coordination among these components in the electricity market structure.

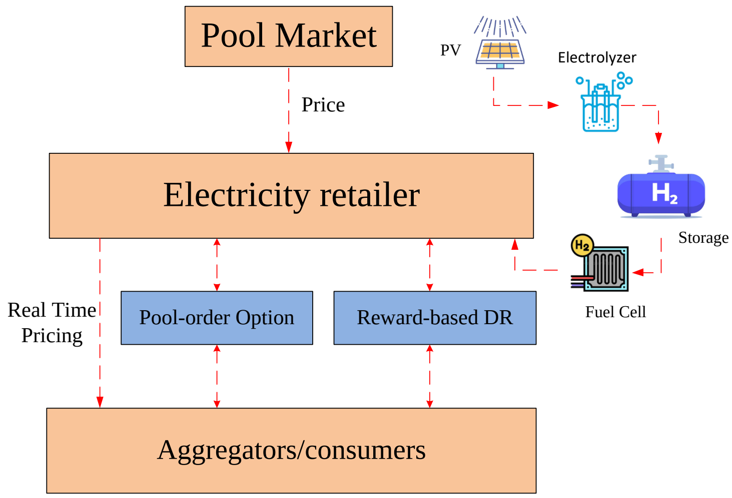

Figure 1: Proposed electricity market structure

3. Model and problem formulation

Figure 2 shows problem modeling for this market. It could be seen that in this electricity market, multi-objective cost minimization is expected for retailers and consumers based on trade-offs between DRPs. These DRPs are traded using a new model to illustrate the daily effect of these programs in monthly operations. The goal of each DRP is to consider both the retailer and consumers simultaneously in the decision-making process. It is assumed that the wholesale price is cleared before this retail market, and uncertainty is considered for this market price data. It is an initial step for newly established electricity markets moving towards deregulated markets. Moreover, the main decision factors in achieving the best schedule are hourly demands, DRPs proposed rewards, hydrogen generation cost, and the pool market price.

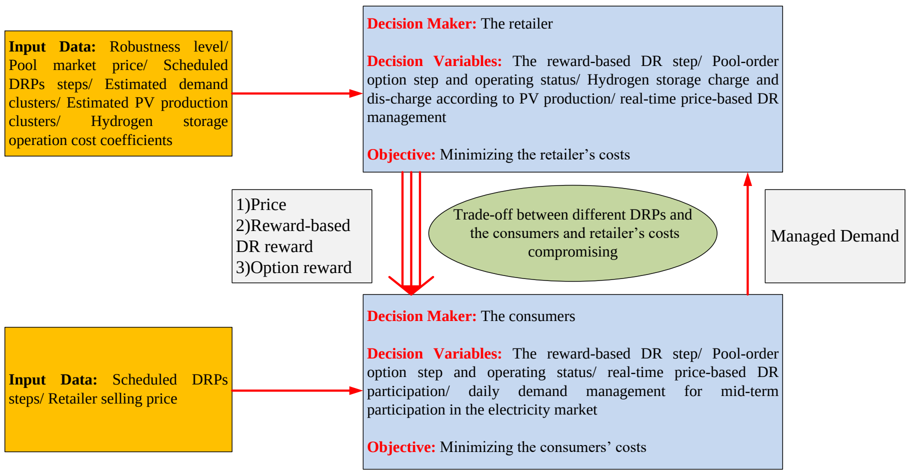

Figure 2: The flowchart of the problem optimization procedure

3.1. DRPs

3.1.1. Pool-order DR (PO)

An option contract is designed for the retailer to participate if the cost of the contract results in more profit than the pool market. The retailer is not forced to implement the option and is authorized to participate in the contract if that generates more profit.The retailer offers four bonus levels and a penalty to consumers when meeting a sudden increase in demand. The retailer has two choices: purchase demand from the wholesale market and pay the penalty, or reduce demand and pay an option bonus. Since the consumer is available anytime to reduce demand, a penalty is considered for the retailer if the wholesale market is selected. It is a viable DRP for electricity markets in developing countries to encourage consumers to collaborate more. Thus, if the pool market price is less than the pool-order option contract price, the retailer pays the penalty to the consumers and purchases the needed power from the pool market. Moreover, the retailer implements the contract if the cost of participation is lower than the cost of purchasing power from the pool market.It should be noted that in this structure, the retailer purchases the needed energy from the wholesale electricity market. Then, calculating the cost of the options leads to a decision to participate. The pool-order option is modeled according to the flowchart shown in Figure 3. In addition, the mathematical modeling of the system is provided in Eqs. 1-4 [19]:

$$\mathrm{Cos\,t}_{poo} = \sum_{m=1}^{N_m} \sum_{poo=1}^{N_{poo}} \begin{bmatrix} P_{poo}(m) . W_{poo}(m) . U_{poo}(m) \\ + (1 - U_{poo}(m)) . Pen_{poo}(m) \end{bmatrix} \tag{1}$$

$$0 \leqslant P_{poo}(m) \leqslant P_{poo}^{Max}(m), \forall poo = 1, 2, \cdots, N_{poo} \tag{2}$$

$$P_{poo}^{total}(m) = \sum_{poo=1}^{N_{poo}} P_{poo}(m) . U_{poo}(m) \tag{3}$$

$$P_{poo}^{total}(m) = \sum_{d=1}^{N_d} \sum_{t \in T_{peak}} P_{m,d,t}^{h,poo} \tag{4}$$

Eq. 1 shows the cost of the pool-order option, which the retailer is confronting, including the penalty that the retailer must pay if the options are not selected; and the cost that the retailer has to pay if the demand decreases. Also, Eq. 2 shows that the participation of the consumers in the option contract is limited to a maximum amount of power. Further, the total amount of the monthly reduced power by the retailer is calculated by Eq. 3. The binary variable in Eq. 3 controls the implementation of the contract. Thus, if the retailer avoids participating in the pool-order option contract, the binary variable would equal zero, and the retailer must pay the consumer's penalty. Eq. 4 represents the demand reduction of peak hours during a month.

3.1.2. Reward-based DR (RB)

In the reward-based DR program, the retailer rewards consumers who participate in the program. The more reduction in power, the more reward is gained by the consumers. The reward amount is calculated according to the amount of reduction, as shown in the curve in Figure 4. Eqs. 5-10 express the mathematical model of this program [18]:

$$\mathrm{Cos\,t}_{rb} = \sum_{i=1}^{N_i} \sum_{m=1}^{N_m} \bar{P}_i^{rb}(m) . Re_i(m) \tag{5}$$

$$P^{rb}(m) = \sum_{i=1}^{N_i} \bar{P}_i^{rb}(m) . U_i^{rb}(m) \tag{6}$$

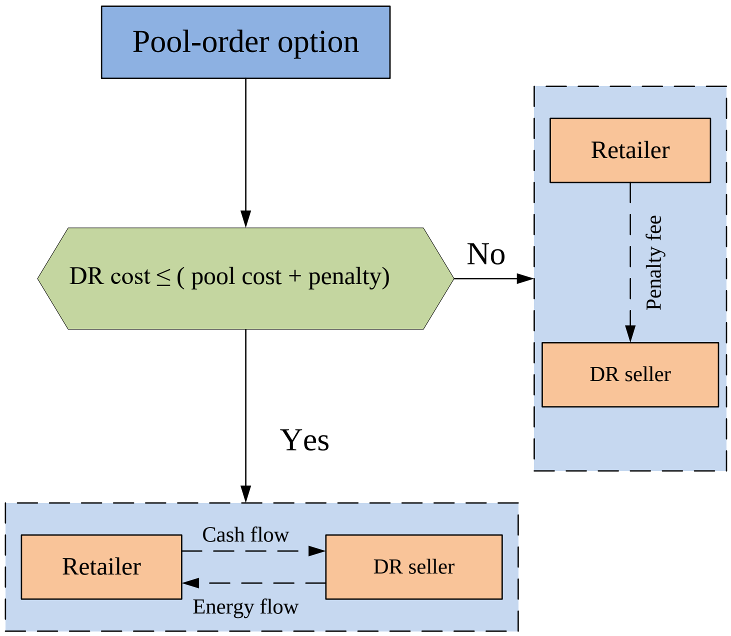

Figure 3: **The schematic model of pool-order demand response**

$$R^{rb}(m) = \sum_{i=1}^{N_i} Re_i(m) \tag{7}$$

$$\bar{R}^{rb}_{i-1}(m).U^{rb}_i(m) \leqslant Re_i(m) \leqslant \bar{R}^{rb}_i(m).U^{rb}_i(m) \tag{8}$$

$$\sum_{i=1}^{N_i} U^{rb}_i(m) = 1 \tag{9}$$

$$P^{rb}(m) = \sum_{d=1}^{N_d} \sum_{t \in T_{peak}} P^{h,rb}_{m,d,t} \tag{10}$$

Eq. 6 indicates the total amount of the monthly reduced power by the consumers. Furthermore, the related reward price is obtained by Eq. 8. Eq. 10 shows how the monthly reduced power is divided into different peak hours. According to Figure 4, a binary variable should be used to indicate which segment of the curve is activated. The activation indicates the amount of the reduced power and the amount of the reward which should be paid to the consumers. In addition, only one of the segments should be activated each month, as defined in Eq. 9.

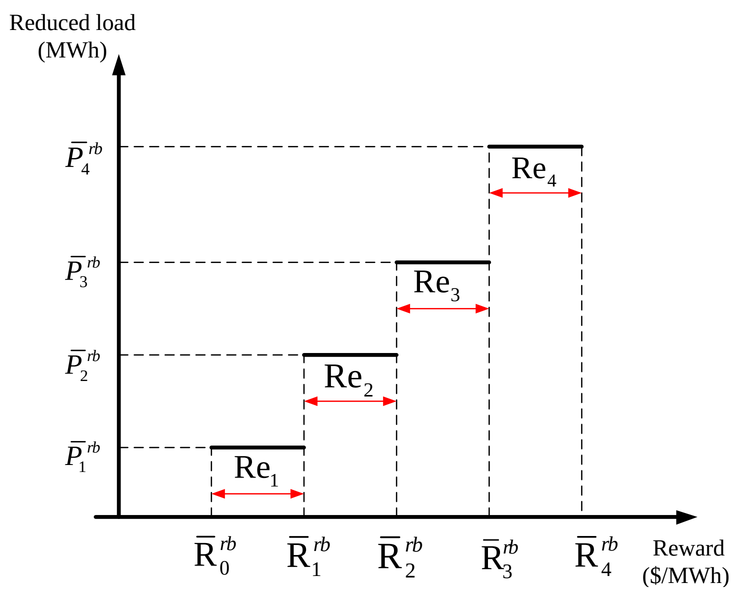

Figure 4: **Reward-based demand response operational curve.**

3.1.3. RTP

Real-time pricing could encourage consumers to shift their loads to hours at lower prices to reduce costs. It is vital to consider that only a specific percentage of consumer demand can be shifted from one hour to another. The real-time price-based DR can be modeled as follows [14]:

$$|RTP_{m,d,t}| \leqslant C_{rtp}.Load_{m,d,t} \tag{11}$$

$$\sum_{t=1}^{N_t} RTP_{m,d,t} = 0 \tag{12}$$

Eq. 11 indicates that only a specific amount of the demand could be shifted, and the parameter C_{rtp} controls this limit. It should be noted that the total shifted demand from peak hours to off-peak hours is equal. Thus, Eq. 12 is considered to satisfy this constraint.

3.2. HS

Integrating ESSs and RES can enormously increase the impact and profitability of these systems. In this case, the ESS is coordinated with a PV in which the PV provides the needed power for the electrolyzer, as expressed in Eq. 13. Moreover, Eq. 14-16 limit the electrolyzer and fuel cell in their bound [37]:

$$P^{el}_{m,d,t} \leqslant P^{pv}_{m,d,t}.U^{el}_{m,d,t} \tag{13}$$

$$P^{el}_{m,d,t} \geqslant P^{Min,el}_{m,d,t}.U^{el}_{m,d,t} \tag{14}$$

$$P^{fc}_{m,d,t} \geqslant P^{Min,fc}_{m,d,t}.U^{fc}_{m,d,t} \tag{15}$$

$$P^{fc}_{m,d,t} \leqslant P^{Max,fc}_{m,d,t}.U^{fc}_{m,d,t} \tag{16}$$

The appeared binary variables in Eq. 13-16 are used to simulate the different working states of the electrolyzer and fuel cell. It should be noted that only one of three states: generating, which is shown by activation of the fuel cell; consumption, which is demonstrated by activation of electrolyzer; and not working state, should be activated. Therefore, Eq. 17 is used to satisfy these conditions in which either one of the binary variables could be equal to one, or both must be equal to zero.

$$U^{fc}_{m,d,t} + U^{el}_{m,d,t} \leqslant 1 \tag{17}$$

The related constraints to the storage are shown in Eqs. 18-20:

$$P^{s}_{m,d,t} = P^{s}_{m,d,t-1} + \eta_{el}.P^{el}_{m,d,t} - {}^{P^{fc}_{m,d,t}}/_{\eta_{fc}} \tag{18}$$

$$P^{Min,s}_{m,d,t} \leqslant P^{s}_{m,d,t} \leqslant P^{Max,s}_{m,d,t} \tag{19}$$

$$P^{s}_{m,d1,t0} = P^{s}_{ini} \tag{20}$$

A linear equation calculates the cost function of the electrolyzer as Eq. 22:

$$F^{el}_{s}\left(P^{el}_{m,d,t}\right) = b^{el}P^{el}_{m,d,t} + c^{el} \tag{21}$$

$$Cos\,t_{el} = b^{el}P^{el}_{m,d,t} + c^{el} \tag{22}$$

The cost function of the fuel cell is modeled by Eq. 23. It is shown that the cost function of the fuel cell is a quadratic function that causes nonlinearity in optimization programming.

$$F^{fc}_{s}\left(P^{fc}_{m,d,t}\right) = a^{fc}\left(P^{fc}_{m,d,t}\right)^{2} + b^{fc}P^{fc}_{m,d,t} + c^{fc} \tag{23}$$

$$F(P) = aP^{2} + bP + c \tag{24}$$

3.3. Proposed linearization method

The necessity of decreasing the calculation volume and obtaining the mixed-integer linear programming (MILP)-based system model is widely used worldwide. Therefore the upper approximation method is considered to get the MILP-based model of the cost function of the fuel cell. In [24, 39], the number of steps for approximation is evaluated by trial and error. It is mentioned that if the number of segments increases, a more accurate approximation is obtained. In this research, the number of segments is evaluated according to the permissible error, which is specified. Moreover, the distance of each segment is determined, and this method is summarized in the algorithm below:

Algorithm
Step 1: First, the linear equation that passes through the beginning and endpoint of the performance area of the fuel cell is calculated.
Step 2: the difference between the linear equation and the quadratic equation is calculated by subtracting the primary cost function of the fuel cell and the linear equation.
Step 3: the maximum error value between the linear equation calculated in **Step 1** and the quadratic cost function is calculated at the performance area. It is the maximum value of the obtained function in **Step 3** at the performance area.
Step 4: The determined point is used to obtain the segments of the linear approximation. The linear equation of the segments is obtained according to the beginning and endpoints of the segments.
Step 5: The maximum value of the error between the linear equations calculated in **Step 4** and each segment's quadratic cost function inbound.
Step 6: If the value of the errors is not less than ε , return to **Step 4**.
Step 7: If the value of errors is less than ε , each segment's beginning and endpoint are obtained according to the error.

After calculating the segments according to the permissible error, Eq . 26-28 are used to determine the cost function of the fuel cell. A binary variable should be considered to activate the segment at which the fuel cell is performing. It should be noted that the number of the “l” is calculated in the algorithm.

$$\begin{cases} F(P) = aP^2 + bP + c \\ P_0 = P_{Min}, \forall P \in [P_{Min}, P_{Max}] \\ \bar{P}_l \end{cases} \tag{25}$$

Finally, the MILP-based model of the quadratic function is expressed in the form of Eq. 26:

$$F(P) = \sum_{l \in N_l} \left(GR_l.\bar{P}_l + I_l.U_l \right) \forall l \tag{26}$$

$$GR_l = \frac{F\left(\bar{P}_l\right) - F\left(\bar{P}_{l-1}\right)}{\bar{P}_l - \bar{P}_{l-1}} \forall l \tag{27}$$

$$I_l = F\left(\bar{P}_l\right) - \frac{F\left(\bar{P}_l\right) - F\left(\bar{P}_{l-1}\right)}{\bar{P}_l - \bar{P}_{l-1}} P \forall l \tag{28}$$

The binary variable is activated, and all other binary variables are deactivated if the performing power is located in a specified segment, which is mentioned in Eqs. 29-30.

$$\bar{P}_{l-1}.U_l \leqslant P \leqslant \bar{P}_l.U_l \forall l \tag{29}$$

$$\sum_l U_l \leqslant 1 \forall l \tag{30}$$

Finally, the cost function of the fuel cell is obtained as Eq. 31. Two steps of this method are shown in Figure 5.

$$Cos\,t_{fc} = \sum_{l \in N_l} \left(GR_l.\bar{P}_l^{fc} + I_l.U_l \right) \forall l \tag{31}$$

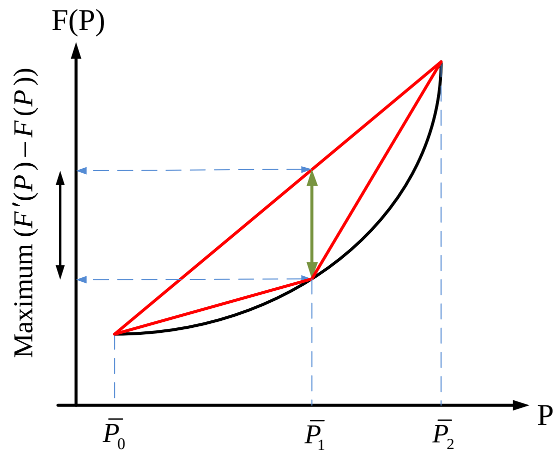

Figure 5: Two steps of quadratic equation linearization steps.

3.4. Power balance

The power balance for the consumers according to their participation in different DR programs is as Eq. 32:

$$P^{p,c}_{m,d,t} = Load_{m,d,t} + RTP_{m,d,t} - P^{h,rb}_{m,d,t} - P^{h,poo}_{m,d,t} \tag{32}$$

Furthermore, the power balance for the retailer is obtained from Eq. 33 as follows:

$$P^{p,r}_{m,d,t} = Load_{m,d,t} + RTP_{m,d,t} - P^{h,rb}_{m,d,t} - P^{h,poo}_{m,d,t} - P^{fc}_{m,d,t} \tag{33}$$

The difference between the power balance equation for the retailer and consumers is the impact of using the HS system, which the retailer controls to enhance its profit. The power reduction in consumer demand at peak hours is limited. Moreover, the RTP only affects the off-peak hours, as mentioned in Eqs. 11-12. The upper limit for power decline at peak hours is modeled as Eq. 34:

$$P^{h,rb}_{m,d,t} + P^{h,poo}_{m,d,t} - RTP_{m,d,t} \leqslant M.Load_{m,d,t} \tag{34}$$

3.5. Costs

3.5.1. Cost of bought power by retailer

The retailer, responsible for providing the demand to the consumers, provides the needed power from the pool market. The cost of purchasing demand from the pool market is obtained by Eq. 35, in which the price is calculated hourly:

$$\mathrm{Cos\,t}_p^r = \sum_{m=1}^{N_m}\sum_{d=1}^{N_d}\sum_{t=1}^{N_t} P_{m,d,t}^{p,r}.W_{m,d,t}^{m} \tag{35}$$

3.5.2. *Cost of bought power by consumers according to RTP*

In RTP, the consumers are approaching an hourly price. In this research, the retailer controls the market price, which multiplies a parameter to the market price that causes changes during peak and off-peak. This parameter is greater than one during peak hours to charge consumers a higher price than the market price. Moreover, the parameter is less than one in off-peak hours to charge consumers less than the market price. This approach encourages consumers to participate in DRPs. In addition, it enhances the system to apply better prices and evaluate its impact on the system. RTP cost in this research is modeled as Eq. 36, which shows the consumers' cost for their demand:

$$\begin{aligned}\mathrm{Cos\,t}_p^c &= \sum_{m=1}^{N_m}\sum_{d=1}^{N_d}\sum_{t\in T_{peak}} P_{m,d,t}^{p,c}.(1+\alpha).W_{m,d,t}^{m} \\ &+ \sum_{m=1}^{N_m}\sum_{d=1}^{N_d}\sum_{t\in T_{off-peak}} P_{m,d,t}^{p,c}.(1-\alpha).W_{m,d,t}^{m}\end{aligned} \tag{36}$$

3.5.3. *Total cost function*

Finally, the retailer's (RC) and consumers' costs (CC) are modeled by Eqs. 37-38, respectively:

$$\mathrm{Cos\,t}_R^{total} = \mathrm{Cos\,t}_p^r + \mathrm{Cos\,t}_{rb} + \mathrm{Cos\,t}_{poo} \tag{37}$$

$$\mathrm{Cos\,t}_C^{total} = \mathrm{Cos\,t}_p^c - \mathrm{Cos\,t}_{rb} - \mathrm{Cos\,t}_{poo} \tag{38}$$

3.6. *Robust optimization*

A typical optimization problem is formulated as Eqs. 39-42:

$$\min \sum_{s=1}^{q} g_s \cdot x_s \tag{39}$$

$$\sum_{s=1}^{n} a_{is} \cdot x_s \leqslant b_i \forall i = 1, \ldots m \tag{40}$$

$$x_s \geqslant 0 \forall s = 1, \ldots, q \tag{41}$$

$$x_s \in \{0,1\} \text{ For some s=1,2,}\cdots\text{,q} \tag{42}$$

As shown in Eqs. 39-42, g_s,a_{is} and b_i are the parameters that could cause uncertainty. In recent years, uncertainty has been modeled in different ways. The RO method assumes that the parameters' probability distribution function (PDF) is unavailable. On the other hand, the bound in which the parameters vary is available. In this case, the$g_s$is varying inbound $[g_s - d_s, g_s + d_s]$, and the $b_i$is varying inbound $\left[b_i - \hat{b}_i, b_i + \hat{b}_i\right]$. Thus, it is vital to consider the bound of variation to achieve robustness against risk. The RO method considers the worst-case scenario to achieve the maximum robustness against risks. According to the optimization problem and its place in it, it is vital to reformulate the problem as Eqs. 43-46 as follows [40]:

$$\textbf{min} \sum_{s=1}^{q} g_s \cdot x_s \tag{43}$$

Subject to:

$$\sum_{s=1}^{n} a_{is} \cdot x_s - b_i + \hat{b}_i.x_{s+1} \leqslant 0 \quad \forall i = 1, \dots m \tag{44}$$

$$x_s \geqslant 0 \, \forall s = 1, \dots, q \tag{45}$$

$$x_s \in \{0, 1\} \text{ For some s=1,2,} \cdots \text{,q} \tag{46}$$

In this formation of the problem, the variable x_{s+1} takes values as one. After considering the uncertainty, the optimization problem turns into Eqs. 47-50 as follows:

$$\textbf{min} \sum_{s=1}^{q} g_s \times x_s + Max \sum_{s=1}^{q} d_s \times |x_s| \tag{47}$$

Subject to:

$$\sum_{s=1}^{n} a_{is} \cdot x_s - b_i + \hat{b}_i.x_{s+1} \leqslant 0 \quad \forall i = 1, \dots m \tag{48}$$

$$x_s \geqslant 0 \, \forall s = 1, \dots, q \tag{49}$$

$$x_s \in \{0, 1\} \text{ For some s=1,2,} \cdots \text{,q} \tag{50}$$

As shown in Eqs. 47-50, the problem is turned into a Min-Max non-linear problem (NLP), which is complicated to solve. Therefore, Sim and Bertsimas's approach is considered to solve this problem. After doing the math according to their approach, the optimization problem is turned into Eqs. 51-60, which can be solved by GAMS software [22, 40].

$$\min \sum_{s=1}^{q} g_s \cdot x_s + z_0 \cdot \Gamma_0 + \sum_{s=1}^{q} O_{0s} \tag{51}$$

$$\sum_{s=1}^{n} a_{is}.x_s - b_i + z_i.\Gamma_i + O_{i,n+1} \leqslant 0 \, \forall i = 1, \ldots m \tag{52}$$

$$z_0 + O_{0s} \geqslant d_s \omega_s \; s \in S_0 \tag{53}$$

$$z_i + O_{i,n+1} \geqslant \hat{b}_i.\omega_{n+1} \; \forall i \neq 0, s \in S_i \tag{54}$$

$$O_{is} \geqslant 0 \; \forall i, s \in S_i \tag{55}$$

$$\omega_s \geqslant 0 \, \forall s \tag{56}$$

$$z_i \geqslant 0 \; \forall i \tag{57}$$

$$-\omega_s \leqslant x_s \leqslant \omega_s \; \forall s \tag{58}$$

$$x_s \geqslant 0 \, \forall s = 1, \ldots, q \tag{59}$$

$$x_s \in \{0, 1\} \text{ For some s=1,2,} \cdots \text{,q} \tag{60}$$

The parameters Γ_0 and Γ_i are used to control the conservativeness of the problem, and they could vary in $[0,|S_0|]$, and $[0,|S_i|]$, respectively. For the risk-neutral approach, the Γ_i=0, and for considering the worst-case scenario, the Γ_i=$|S_i|$ should be considered. $z$and $O_s$are introduced by the strong duality theorem.

3.7. Objective function

DRPs enormously affect different parts of the system's behavior. In this research, the objective function contains consumer and retailer costs, considering a multi-objective optimization using weighting factors [4]. In this case, the trade-off between DRPs is supposed to evaluate the exact effect of different programs in different situations. The price, advertisements, and society's various aspects can easily change the consumer's attitude toward economic decisions. The objective function is to obtain a valid point of view on the system behavior, formulated as Eq. 61. After doing the mathematical operations, the formulation is turned into Eq. 65:

$$\begin{aligned} \min z = \rho \left(\text{Cos}\, t_p^r + \text{Cos}\, t_{rb} + \text{Cos}\, t_{poo} + \text{Cos}\, t_{fc} + \text{Cos}\, t_{el}\right) \\ + (1-\rho) \, . \left(\text{Cos}\, t_p^c - \text{Cos}\, t_{rb} - \text{Cos}\, t_{poo}\right) \end{aligned} \tag{61}$$

$$\begin{aligned}\mathbf{min}\ z = \rho\left(\mathrm{Cos}\,t_p^r + \mathrm{Cos}\,t_{rb} + \mathrm{Cos}\,t_{poo} - \mathrm{Cos}\,t_p^c + \mathrm{Cos}\,t_{rb} + \mathrm{Cos}\,t_{poo} + \mathrm{Cos}\,t_{fc} + \mathrm{Cos}\,t_{el}\right)\\ + \left(\mathrm{Cos}\,t_p^c - \mathrm{Cos}\,t_{rb} - \mathrm{Cos}\,t_{poo}\right)\end{aligned} \tag{62}$$

$$\begin{aligned}&= \rho\left(\mathrm{Cos}\,t_p^r + \mathrm{Cos}\,t_{fc} + \mathrm{Cos}\,t_{el} - \mathrm{Cos}\,t_p^c + 2\,\mathrm{Cos}\,t_{rb} + 2\,\mathrm{Cos}\,t_{poo}\right)\\ &+ \left(\mathrm{Cos}\,t_p^r - \mathrm{Cos}\,t_{rb} - \mathrm{Cos}\,t_{poo}\right)\end{aligned} \tag{63}$$

$$= \rho.(\mathrm{Cos}\,t_p^r + \mathrm{Cos}\,t_{fc} + \mathrm{Cos}\,t_{el}) + (1-\rho)\,.\,\mathrm{Cos}\,t_p^c + (2\rho - 1)\,.\,\mathrm{Cos}\,t_{poo} + (2\rho - 1)\,.\,\mathrm{Cos}\,t_{rb} \tag{64}$$

$$= \rho.(\mathrm{Cos}\,t_p^r + \mathrm{Cos}\,t_{fc} + \mathrm{Cos}\,t_{el}) + (1-\rho)\,.\,\mathrm{Cos}\,t_p^c + \beta.\,\mathrm{Cos}\,t_{poo} + \gamma.\,\mathrm{Cos}\,t_{rb} \tag{65}$$

3.8. Ultimate formulation

In this case, Eq. 13 is turned into Eqs. 66-67 to apply the robust approach because the binary variable should be separated to obtain the robust formation. Further, Eq. 67 controls the electrolyzer if the binary variable is zero.

$$P^{el}_{m,d,t} \leqslant P^{pv}_{m,d,t} \tag{66}$$

$$P^{el}_{m,d,t} \leqslant M.U^{el}_{m,d,t} \tag{67}$$

Finally, the robust form of the objective function is obtained as Eqs. 68-76 as a robust multi-objective optimization problem. This is a generalizable and customizable model for other new electricity markets to enhance their market step by step.

To generalize this modeling to other new electricity markets, it could be noted that in addition to the flexibility of analyzing DRPs separately and minimizing retailer and consumer costs, this model enables the operator to optimize a combination of these components. Different energy sectors, including generators, retailers, and consumers, have integrated into this system for optimal multi-objective market planning. For emerging SESs, one-dimensional optimization is unacceptable, so all stakeholders will benefit from this multilateral collaboration. As a result of this linear, commercial, and robust model, investors are encouraged to cooperate, and their profits are highly reliable. Moreover, other RES could be added to this system based on their potential in other regions.

$$\begin{aligned}\mathbf{min}\ F = \rho\left(\mathrm{Cos}\,t_p^r + \mathrm{Cos}\,t_{fc} + \mathrm{Cos}\,t_{el} + z_0.\Gamma_0 + \sum_m\sum_d\sum_t O_{0,m,d,t}\right)\\ + (1-\rho)\,\mathrm{Cos}\,t_p^c + \beta.\,\mathrm{Cos}\,t_{poo} + \gamma.\,\mathrm{Cos}\,t_{rb}\end{aligned} \tag{68}$$

$$P^{el}_{m,d,t} + z_{1,m,d,t}.\Gamma_{1,m,d,t} + O_{1,m,d,t} \leqslant P^{pv}_{m,d,t} \tag{69}$$

$$z_0 + O_{0,m,d,t} \geqslant W^{m,var}_{m,d,t}.\omega_{0,m,d,t} \tag{70}$$

$$z_{1,m,d,t} + O_{1,m,d,t} \geqslant P^{pv,var}_{m,d,t}.\omega_{1,m,d,t} \tag{71}$$

$$-\omega_{1,m,d,t} \leqslant 1 \leqslant \omega_{1,m,d,t} \tag{72}$$

$$-\omega_{0,m,d,t} \leqslant P^{p,r}_{m,d,t} \leqslant \omega_{0,m,d,t} \tag{73}$$

$$O_{0,m,d,t}, O_{1,m,d,t} \geqslant 0 \tag{74}$$

$$z_0, z_{1,m,d,t} \geqslant 0 \tag{75}$$

$$P^{p,r}_{m,d,t}, P^{el}_{m,d,t} \geqslant 0 \tag{76}$$

4. Results and discussion

4.1. Data

This study assumes a small part of the demand in Iran (about 0.1%, 2019) to solve the problem quickly [11]. The hourly demand for four months is presented in Figure 6. February (M1), May (M2), August (M3), and November (M4) are selected to analyze, and each month is categorized into three clusters (C1, C2, and C3). Pool market price is an uncertain variable in this problem. Purchase and sell prices for the retailer are separated. It is assumed that deterministic prices are prepared for consumers. However, uncertainty is considered in purchasing electricity from the pool market. RO minimizes the retailer risk in this regard, and Figure 7 shows the market price for consumers.

Each month has four pool-order options, with a specific volume of demand and a negotiated price for each option. The maximum demand in the option contract is 200 MW. The penalty depends on the cost of the contract option and the period for which it is set, and 15% of the contract cost is considered a penalty. The four option bonus prices are shown in Figure 8. In RB, consumers will be rewarded for each amount of load reduction. In this study, 13 steps are considered for the paid reward to consumers for each demand reduction per month, as shown in Figure 9.

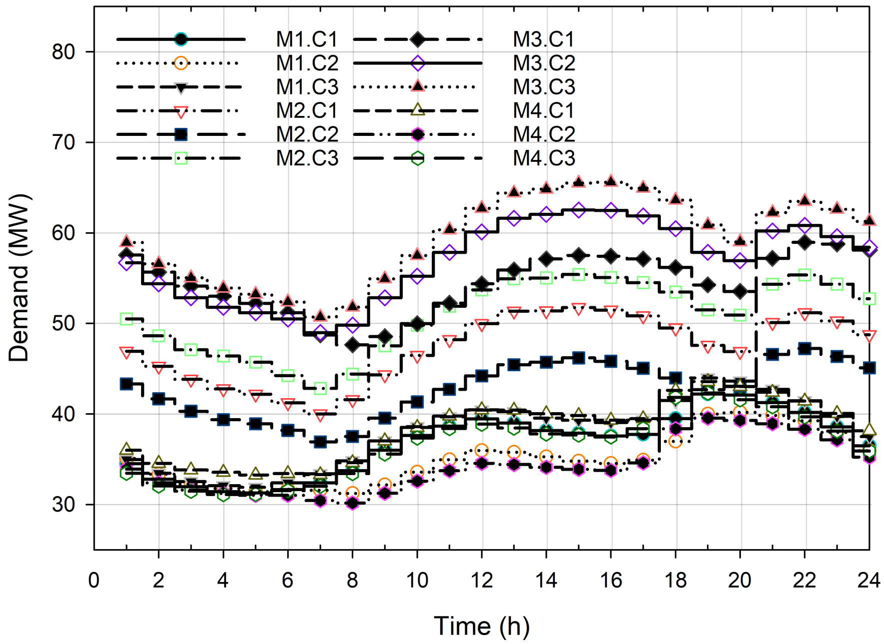

Figure 6: Hourly demand for four different months and clusters.

PV generation is the second uncertain parameter. According to the literature review and the stochastic nature of solar energy, uncertainty is considered in PV generation. In fact, the study area (Hormozgan province) is situated in southern Iran at a latitude of 25 north and a longitude of 52 east. It has a hot and humid climate as a port near the equator. Factors, such as global horizontal irradiance (GHI), can determine site suitability. In Iran, solar PV installations are selected in areas with at least 1700 kWh/m2 of average annual solar radiation [2]. A five MW PV system output is shown in Figure 10, and it supplies electrolyzer electricity demand for green hydrogen production.

4.2. Simulation results and discussion

The problem is MILP, which is solved using the CPLEX solver in GAMS with a relative gap equal to zero to reach the optimal global solution [41]. Analysis of the

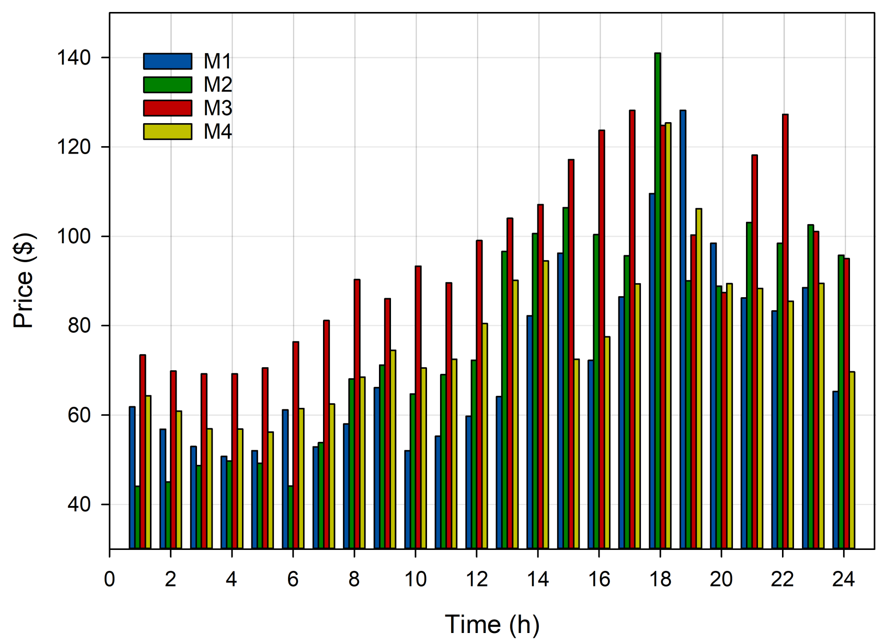

Figure 7: **Pool market price of the system in each month.**

results is divided into three cases:

- **CS0**: without DRPs and RO.
- **CS1**: with DRPs and without RO (deterministic pricing).
- **CS2**: with DRPs and RO.

4.2.1. ***CS1***

Figure 11 shows the cost analysis of the performance of RB and PO without considering RO. β is the coefficient of PO (γ=0.7), which is assumed to change to analyze the trade-off between this contract and others, and γ is the coefficient of RB (β=0.7), this is the base point, and trade-off analyses are applied around this point). It is necessary to solve this multi-objective optimization to gain an optimal trade-off between DRPs. Increasing β and γ are profitable for the retailer, while RB

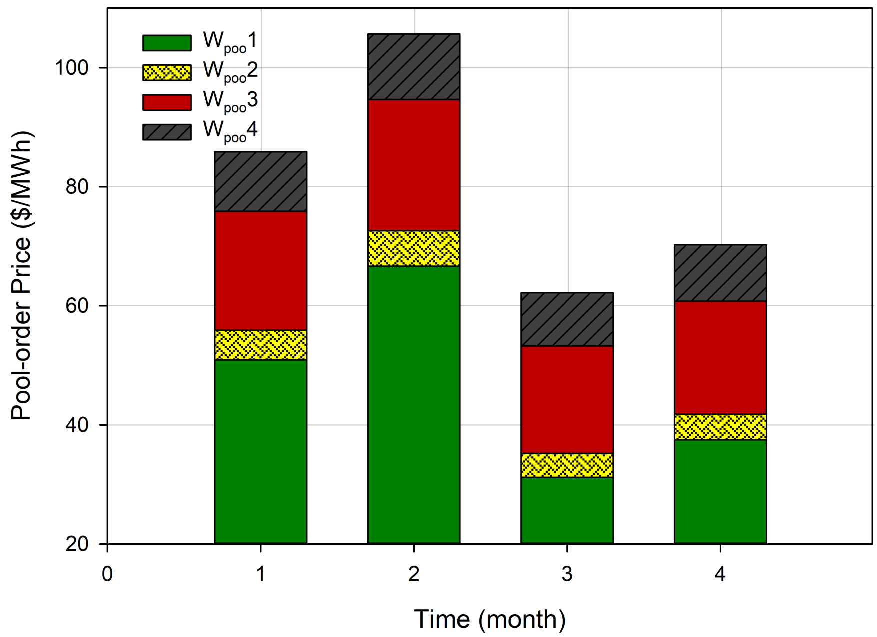

Figure 8: **Pool-order option prices for each month.**

has more cost reduction. Further, changing parameters have a greater impact on CC (3% and 14% for RC and CC, respectively). It is demonstrated that from γ =0.5 to 1, the retailer should plan to promote this program to persuade consumers to collaborate. On the other hand, there are two scenarios for consumers. If they can affect the coefficients, they will pay less if the γ is less than 0.5; hence they should choose RB. Participating in PO is more profitable for them if they have to follow the retailer policies, for (β more than 0.5. Moreover, α is set to 0.1 in these analyses. The retailer's attention to scheduling to achieve these goals directly impacts its profit and reliability. Furthermore, this policy can affect consumer behavior and change their priorities in line with the retailer's plans. The retailer could forecast the hydrogen demand and DRPs performance through this analysis. So, they could invest in the best direction to maximize their profit and propose diverse plans to consumers.

Only the summer results are shown due to the similarity of the results in each

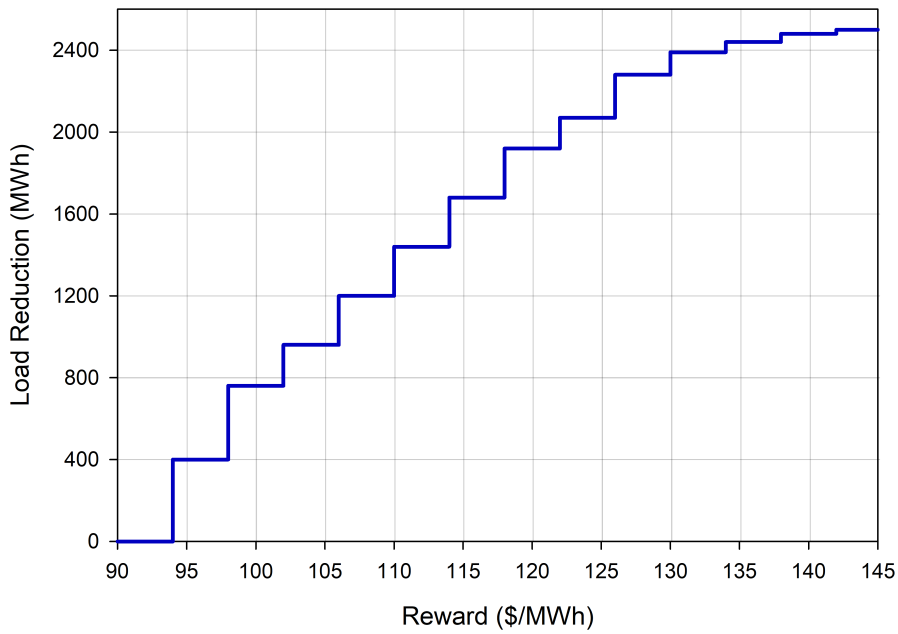

Figure 9: **Paid reward steps for load reduction in reward-based demand response per month.**

of the different seasons (although the data are different in different seasons of the year, the results obtained from their comparison have almost the same trend), and to avoid the complexity of the figures. Because in summer, there is the most solar radiation (Figure 10), the most demand, and the longest peak hours, and it is the most critical season. The performance of the electrolyzer and FC in summer is shown in Figure 12, and the production of the electrolyzer is controlled by solar potential. Daily electrolyzer consumption is almost 23.87 MWh. FC is a suitable backup and reserve for the system at a lower cost, and it could supply the demand in peak hours to contribute to RC reduction. This analysis can encourage investors in the hydrogen industry of developing countries' electricity markets.

4.2.2. ***CS2***

Risk-averse decision-making is possible after applying RO. Analysis of programs is shown in Figure 13. According to the figure, the changes have fluctuations, par-

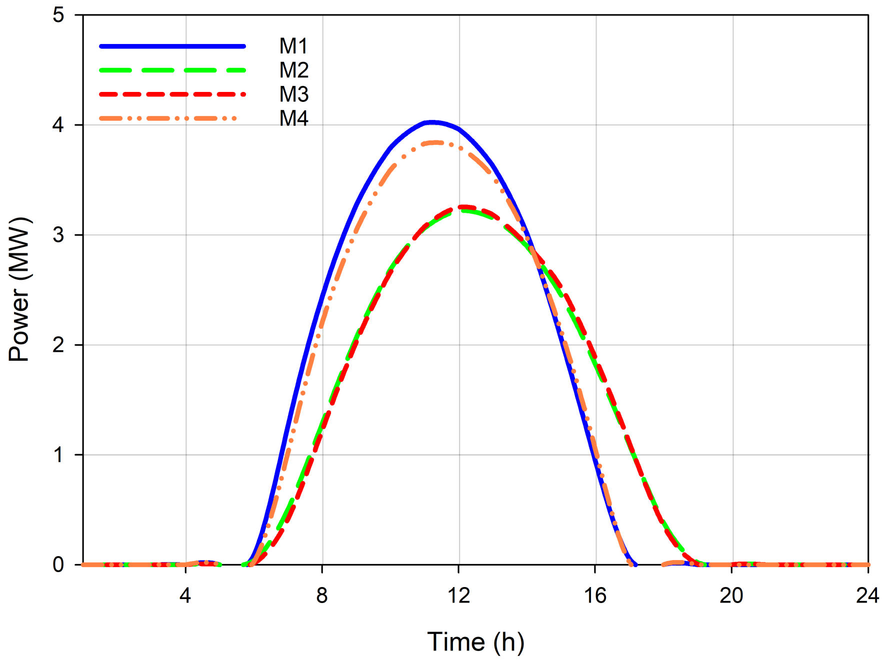

Figure 10: **PV power plant generation.**

ticularly for consumers. The RC and CC changes are almost 2.8% and 11%, respectively. In this case, the retailer cost is minimized for β more than 0.7. Consumers should have three plans. For γ =0.3 and more than 0.7, collaboration in RB is the best choice, while for β between 0.3 and 0.7, PO is considerably more beneficial and reliable. Consumers have a remarkable correlation with the retailer's behavior and pricing; hence consumers have to behave this way when the retailer has a risk-averse strategy. By RO approach, Figure 14 indicates the performance of the green hydrogen system in summer. , robust PV generation for electrolyzer is 14.19% lower than in **CS1**. Due to this limitation, FC's contribution is affected, which is another reason for the increasing RC in **CS2** compared to **CS1** (Table 2).Of fluctuations in these results, decision-making would be complicated, particularly for consumers. Consumers' preference follows the retailer's policies. For example, for β= 0.6 and β = 1, there is a nearly 10% difference in consumer costs. On the other

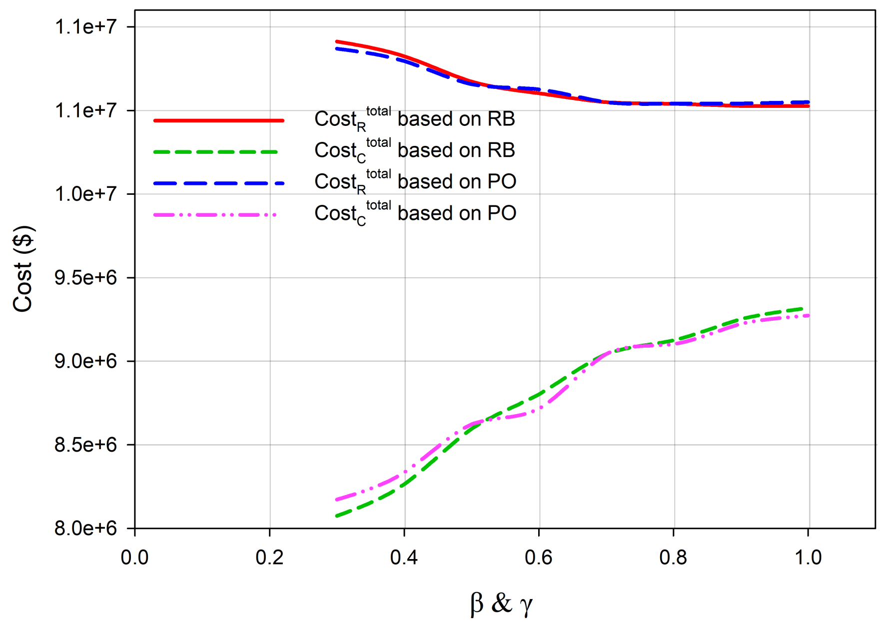

Figure 11: **Trade-off of demand response programs with deterministic pricing.**

hand, the retailer should consider that its benefit depends on consumers' collaboration in DRPs. Thus, this is the trade-off between market players to attain win-win operational planning.

Figure 15 represents the analysis of the RTP program. These are figures without RO (**CS1**) and RO (**CS2**) cases ($\beta = \gamma = 0.7$). As mentioned in section 3.5.2 , the price in peak hours is more than the market price and in off-peak hours is less than the market price. Hence, increasing α is not effective in CC reduction. Consumers prefer to pay less during peak hours to gain more benefits. In **CS1** and **CS2**, the contribution of RTP to CC changes by 3.99% and 3.22%, respectively. Table 2 shows the comparison between cases. DRPs reduce the RC by 5.57%, whereas CC is reduced by 1.76% compared with **CS1**. Further, the retailer could expect 5.32% savings in cost if RO is implemented. Pricing is a tool the retailer wants to reduce their risk in the first preference. RTP provides an opportunity for retailers in emer-

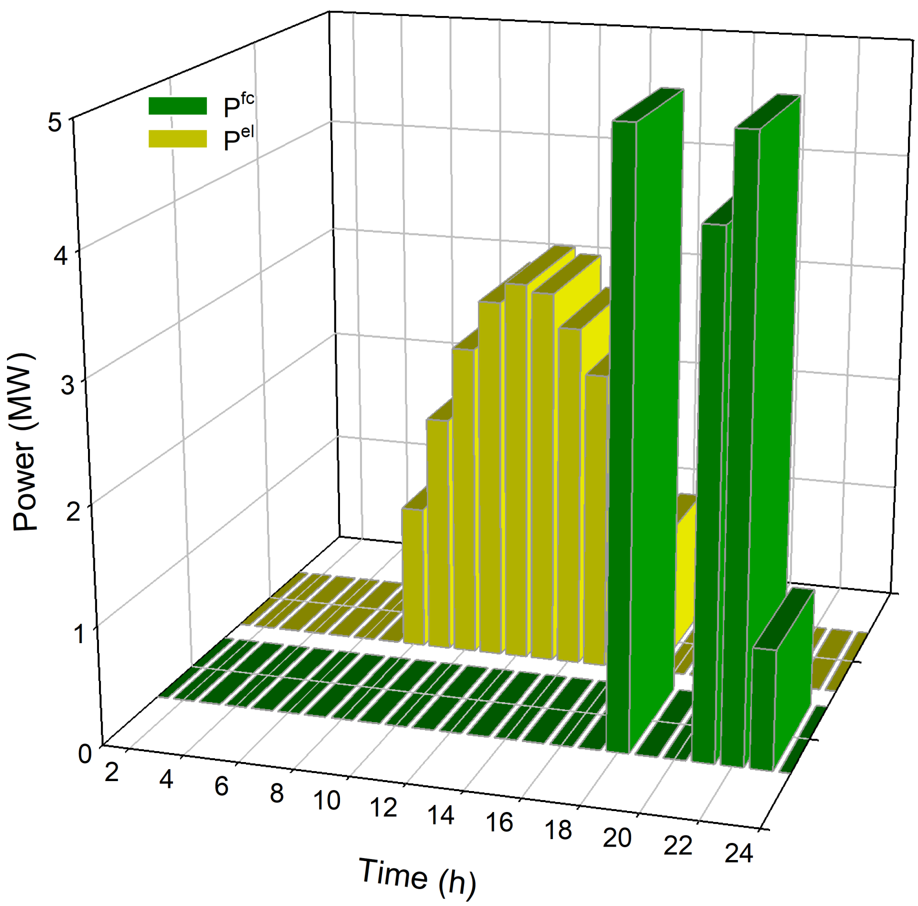

Figure 12: **Hydrogen storage performance in CS1.**

gency times like peak hours to reduce their profit to supply the market. Also, RTP enables them to analyze DRPs for future contracts with a robust approach. The risk-averse strategy could reduce the cost, meaning that these goals are optimized simultaneously. Therefore, pricing is important when decision-making. Therefore, the trade-off for DRPs is crucial for decision-making and pricing plans. The retailer could maximize advantages with minimum risk.

The robustness of the objective function is shown in Figure 16. Γ_0 is considered for the pool market price RO parameter, while $\Gamma_{1,m,d,t}$ is considered for PV generation uncertainty modeling [0, 2880]. Moreover, robustness increases RC by 0.27%

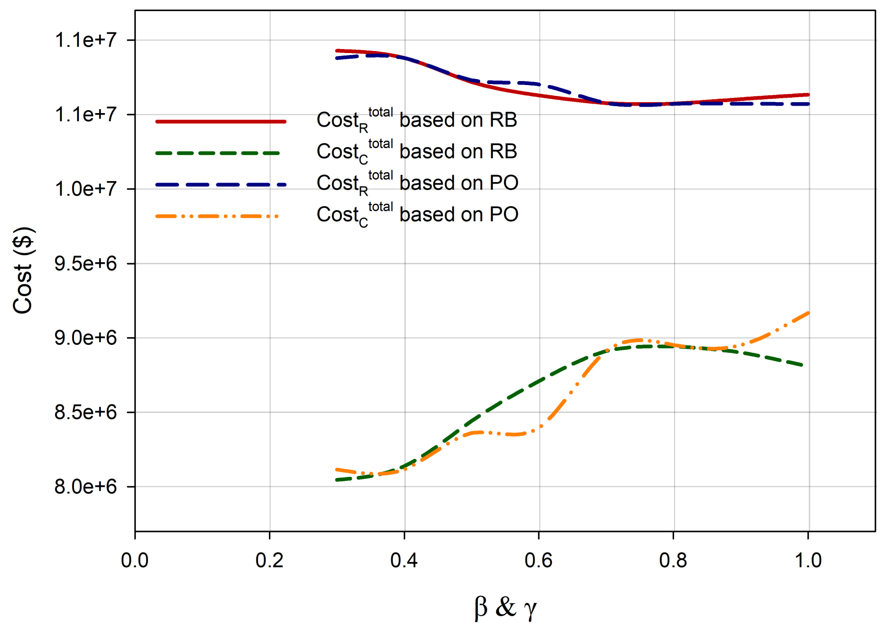

Figure 13: **Trade-off of demand response programs considering robust optimization.**

and encourages consumers to participate in DRPs due to the 1.47% CC reduction. Further, Table 3 shows RB and PO share in CC reduction. More than 70% of the profit was from the implementation of PO. In the maximum RO, the total portion of DRPs increased by 0.89%. Therefore, it can be concluded that that collaborating in DRPs is necessary and effective in persuading consumers and can provide a risk-averse plan for the retailer. This modeling is adjustable and validated for different market structures and policies.

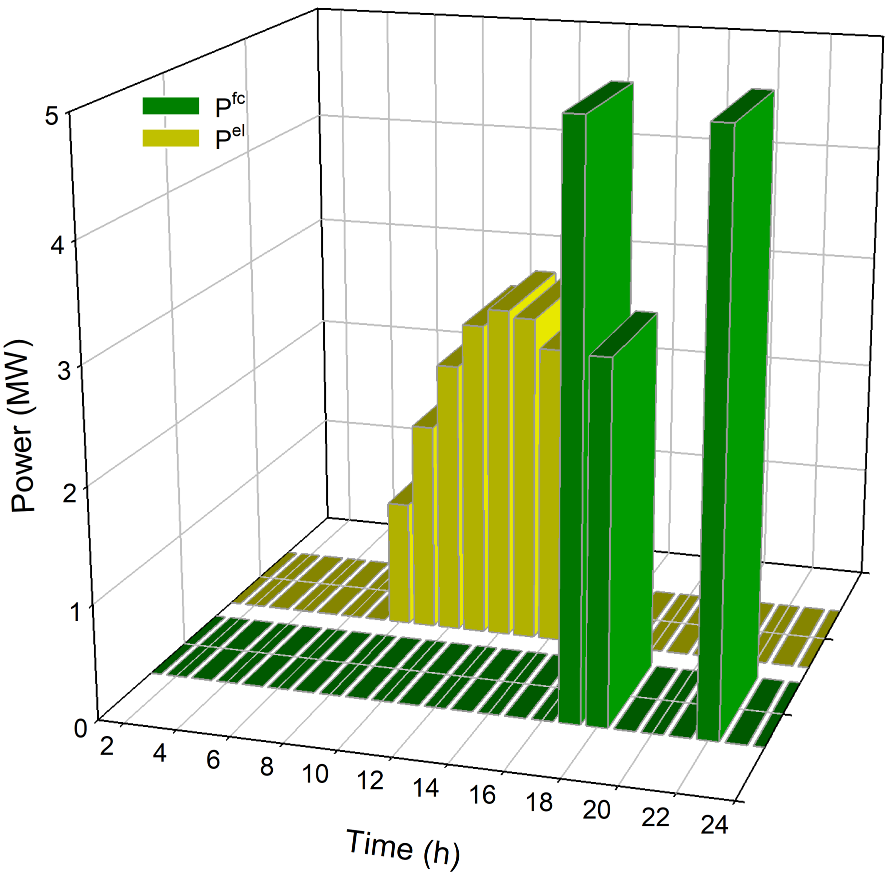

Figure 14: Performance of hydrogen storage system in CS2.

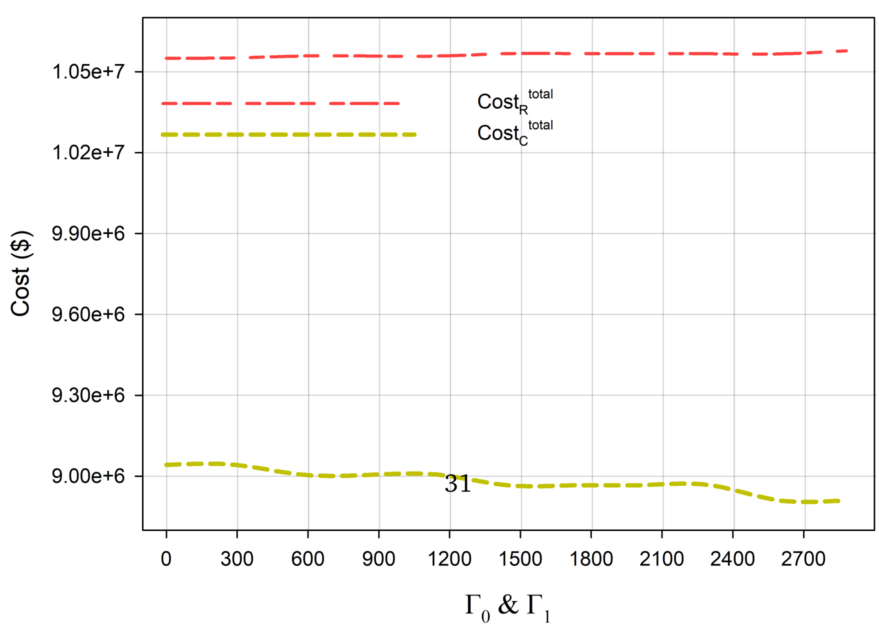

Figure 16: Analysis of the impact of robust optimization on consumer and retailer costs.

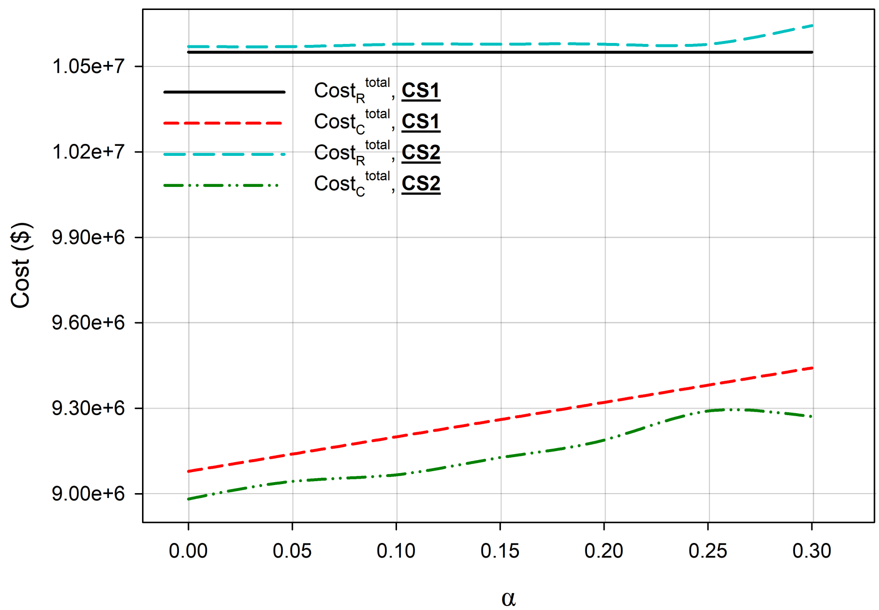

Figure 15: **Results of implementing real-time pricing in CS1 and CS2.**

Table 3: **Share of demand response programs in consumers' costs reduction.**

Γ_0 & $\Gamma_{1,m,d,t}$	CC ($)	RB Income ($)	PO Income ($)	RB Share (%)	PO Share (%)	Total CC Reduction (%)
0	9199697.72	237520	633452	2.38	6.39	8.77
576	9162701.88	260160	634520	2.62	6.4	9.02
1152	9162643.19	260160	634520	2.63	6.41	9.04
1782	9123547.88	237520	679848.8	2.41	6.88	9.29
2304	9123934.39	237520	679848.8	2.4	6.87	9.27
2880	9066304.98	272960	679848.8	2.77	6.89	9.66

Figures 17 to 20 show the peak-shaving and load-shifting of the system each month. Further, the demand of all clusters in **CS2** is compared with **CS0**, and the peak-shaving in all months has appropriately happened. There is an average reduc-

Table 2: Summary of costs changes in different cases.

Case	RC($)	RC Reduction(%)	CC ($)	CC Change (%)
CS0	11171712.67	–	7608254.51	–
CS1	10549976.10	5.57	9199697.72	20.92
CS2	10577934.96	5.32	9066304.98	19.16

tion of 2.2 MW in the difference between the maximum and minimum demand in the winter and almost 2.7 MW in the spring. However, due to the decrease in minimum demand, this indicator has increased by 2.3 MW in the summer, while for M4, it has increased by 0.5 MW. Peak-shaving is viable support for RES generation. The shifted load could be supplied by PV during the daytime, and ESS's cost reduction is the following benefit.

To further discuss, this research is conducted on Iran's newly launched electricity market. As a result, it showed the demand management based on criteria needed in the market structure. The smoothness obtained from using different DRPs affects different parts' behavior in the power system. Using the results, the retailers could manage their budget and invest in the energy sector to secure more profit. Also, the consumers benefit from the DRPs mentioned in this research, and by driving their daily demand, they could participate in the mid-term DRPs. On the other hand, retailers could use the results of this research and regulate the price to obtain more profit. However, the price could affect consumers' participation in the mid-term DRPs and consequently affect the retailers' profit. Considering the uncertainty using the RO method enhances the reliability and confidence level of the decision-makers, so they can invest and regulate their activities in the system using the conservativeness created by this method. This approach could be generalized to other countries. Also, the evaluation could be obtained by modeling different components or DRPs rather than those used in this research.

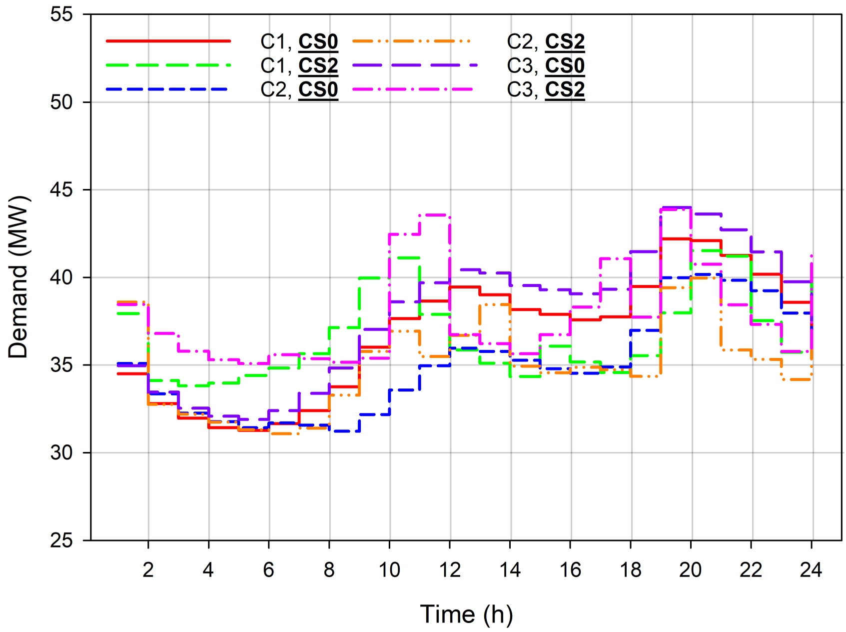

Figure 17: **The effect of demand response programs and robust optimization on M1.**

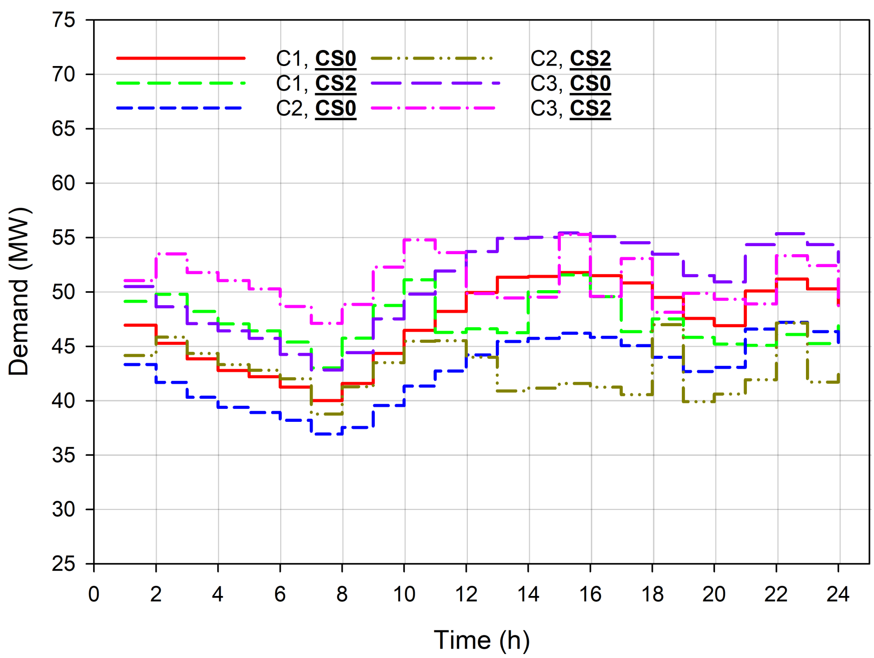

Figure 18: **The effect of demand response programs and robust optimization on M2.**

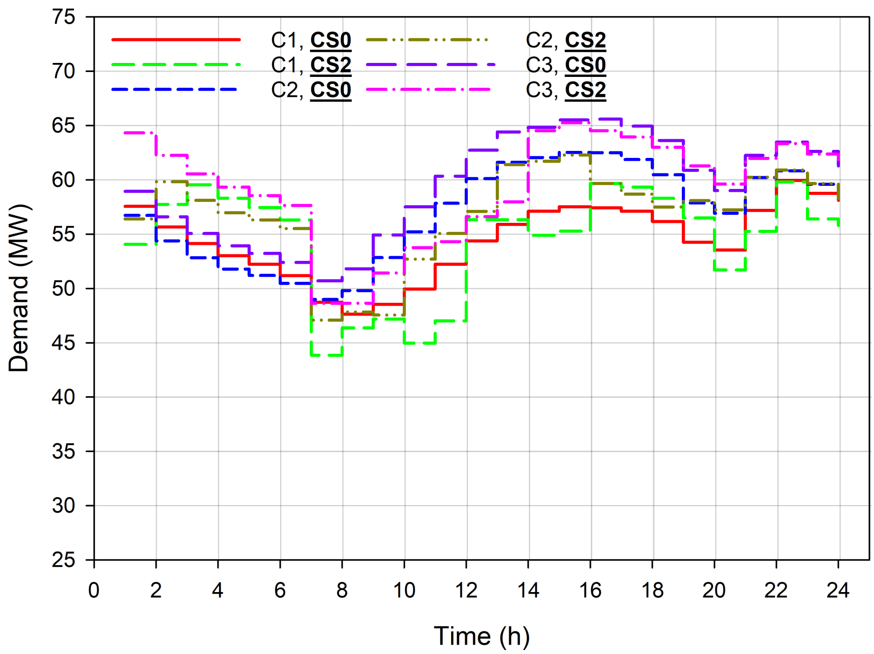

Figure 19: The effect of demand response programs and robust optimization on M3.

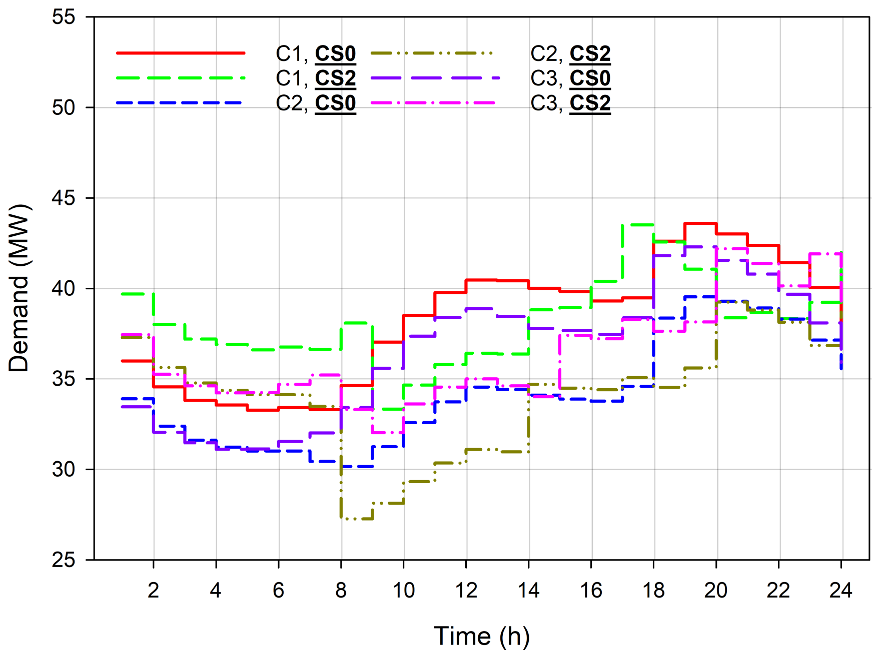

Figure 20: The effect of demand response programs and robust optimization on M4.

5. Conclusion and future work

The world is looking forward to consuming optimal sustainable energy. Smart energy systems (SESs) have been introduced due to the increasing challenges of energy systems. Therefore, the SESs players should actively contribute to the electricity market to fulfill these aims. Further, various policies could be imposed for consumers and retailers to minimize costs. Numerous demand response programs (DRPs) have been introduced for both market players to satisfy their goals. In this context, many countries worldwide are trying to reach a zero-carbon SES because of global warming and environmental threats. Global warming mitigation using renewable energy sources (RESs) has become more cost-effective in recent years. Iran has a great opportunity to decarbonize its energy system because of the abundant availability of solar energy. Along with this, energy storage systems (ESSs) should be integrated to improve the performance and reliability of RESs. From a long-term perspective, the hydrogen industry is an essential part of future SESs, which could use as the best ESS in Iran's conventional energy system. A reliable market scheduling integrated with variable parameters must resist price and RESs uncertainties. The robust optimization (RO) is applied to this problem to model uncertainties of PV generation and pool market prices. RO obtains a more reliable, accurate, and faster solution than the scenario-based approach. A generalized mid-term planning could be the core problem of newly launched electricity markets worldwide. As the Iranian electricity market has just been established, this market needs to be analyzed carefully to reach a dynamic structure. Reward-based demand response (RB), pool-order option (PO), and real-time pricing (RTP) are implemented in the system for these objectives, while green hydrogen is considered. This research utilized MILP, while the fuel cell (FC) cost function is quadratic. Thus, a linearization method is defined in this study with more accurate modeling than other methods. α, β, and γ control the multi-objective function of this study.These parameters enable retailers and consumers to select the best DRP based on their goals. The trade-off between DRPs is modeled. It is possible to analyze the impact of DRPs individually or a combination of them. ρ is the cost-minimizing weight for the retailer and

1- ρ is considered for consumers. So, the expectation of both players could be derived simultaneously. This could be considered a robust socio-economic approach in the electricity market.The main decision factors in attaining the best schedule are hourly demands, DRPs proposed rewards, and hydrogen generation cost.

The results are divided into three cases. In **CS1**, the retailer should encourage people to collaborate in RB. However, after RO, PO is more beneficial to the retailer. The retailer wants to reduce the risk via pricing as the first preference. The risk-averse strategy also reduces costs, meaning all of their goals are met at the same time, proving how crucial pricing is when making decisions. Further, the integration Integration of green ESS has an acceptable performance in this application for progress toward SESs, while FC in peak hours contributes to peak-shaving. In , the power consumed by the electrolyzer is decreased by 14.19% because of robust PV generation. Mid-term scheduling of ESS in this study paves the way for the hydrogen industry in the future. Affordable hydrogen energy convinces communities to form their policies in this manner. In future improvements, the pricing issues and the power systems' constraints can be considered to look through the subject from the reliability point of view, the impact of integrating hydrogen vehicles, consumer behavior, and their features, and analyzing environmental goals in this regard. Finally, the main results are summarized as follows:

- In **CS1**, the retailer's preference is to promote RB. However, in **CS2**, PO is more beneficial to their goals.
- In **CS1** and **CS2**, the retailer's cost is reduced by 5.57% and 5.32%, respectively.
- By analyzing the system's daily operation and from the consumers' view, PO contributes 70% in cost minimization.
- The share of DRPs in consumers' costs reduction in **CS1** and **CS2** is 8.77% and 9.66%, respectively.

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CRediT authorship contribution statement

Reza Khalili: Data curation, Visualization, Software, Writing - original draft. **Arian Khaledi**: Writing - original draft, Investigation, Software. **Mousa Marzband**: Conceptualization, Supervision, Methodology. **Amin Foroughi Nematollahi**: Writing - review & editing. **Behrooz Vahidi**: Review & editing, Validation. **Pierluigi Siano**: Supervision, Conceptualization.

Declaration of competing 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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