Optimal Stochastic Conditional Value at Risk-based Management of a Demand Response Aggregator Considering Load Uncertainty

Morteza Vahid-Ghavidel
FEUP and INESC TEC
Porto, Portugal
mv.ghavidel@gmail.com

Mohammad Sadegh Javadi
INESC TEC
Porto, Portugal
msjavadi@gmail.com

Sérgio F. Santos
INESC TEC and UPT
Porto, Portugal
sdfsantos@gmail.com

Matthew Gough
FEUP and INESC TEC
Porto, Portugal
mattgough23@gmail.com

Miadreza Shafie-khah
University of Vaasa
Vaasa, Finland
mshafiek@univaasa.fi

João P. S. Catalão
FEUP and INESC TEC
Porto, Portugal
catalao@fe.up.pt

2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe) | 978-1-6654-3613-7/21/$31.00 ©2021 IEEE | DOI: 10.1109/EEEIC/ICPSEurope51590.2021.9584827

***Abstract*—This paper models a novel demand response (DR) trading strategy. In this model, the DR aggregator obtains the DR from the end-users via two types of DR programs, i.e. a time-of-use (TOU) program and an incentive-based DR program. Then, it offers this DR to the wholesale market. Three consumer sectors, namely residential, commercial and industrial, are included in this problem. The DR program is dependent on their corresponding load profiles during the studied time horizon. This paper uses a mixed-integer linear programming (MILP) problem and it is solved using the CPLEX solver through a stochastic programming approach in GAMS. The risk measure chosen to represent the load uncertainty of the users who are participating in the DR program is Conditional Value-at-Risk (CVaR). The proposed problem is simulated and assessed through a case study of a test system. The results indicate that the industrial loads play a major role in the power system and this directly affects the DR program. Moreover, the risk-averse decision-maker in this model favors a reduced participation in the DR programs when compared to a decision-maker who is risk-neutral, since the risk-averse decision maker prefers to be more secure against uncertainties. In other words, an increase in risk factor results in a decrease in the participation rate of the consumers in DR programs.**

***Keywords*—Conditional Value at Risk (CVaR), Demand response, DR aggregator, Stochastic programming, Risk management, Time-of-use (TOU).**

Nomenclature

Indices

t	Time
j	Incentive-based DR step
p	Period
c	Consumer
ω	Scenarios

Parameters

$D_0(c,t)$	Initial demand [MW]
$E(c,t,p)$	Elasticity matrix
$\lambda_0(c,p)$	Initial price [€/MWh]
$\lambda(c,p)$	TOU price [€/MWh]
ρ	The confidence level
$\bar{P}_j^{DR}(t)$	Load reduction step in the incentive-based DR [MW]
$\bar{R}_j^{DR}(t)$	Incentive step in the incentive-based DR [€/MWh]
$PF(\omega,t)$	Load participation factor

Variables

β	The risk factor
$P^{TOU}(t)$	TOU volume [MW]
$P^{DA}(t)$	Traded power in DA market [MW]
ξ	Auxiliary variable for CVaR calculation
$\eta(\omega)$	Auxiliary variable for CVaR calculation

Binary Variables

$v_j^{DR}(t)$	Step in the incentive-based DR

J.P.S. Catalão acknowledges the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under POCI-01-0145-FEDER-029803 (02/SAICT/2017). M. Vahid-Ghavidel acknowledges the support of FCT for the Ph.D. individual scholarship 2020.08822.BD.

I. Introduction

Demand response (DR) programs have the potential to provide flexibility and increase reliability, as well as reducing emissions caused by power generation. The primary objective of a DR program is to reduce the strain on the power system when there is a high demand or peak periods through altering the energy consumption of the users.

Due to the low amount of DR resource of most consumers, especially concerning commercial and residential users, these consumers are not allowed to trade DR at a wholesale market level. A DR aggregator combines the offers of these smaller users to participate in wholesale markets. The aggregation, optimization, and operation of DR from the consumers who choose to participate in the DR programs is then the responsibility of the DR aggregator [1].

The DR aggregator participates in electricity markets and reschedules the consumption patterns of the consumers to maximize the profit obtained from participating in the DR programs or minimizing the total cost of energy consumption through DR employment. DR programs are now playing an important role not only in the electricity markets but also in heating and gas markets thus, DR programs are being increasingly used in multi-energy systems. This may increase the profit of the aggregator and provide more flexibility to the consumers [2].

978-1-6654-3613-7/21/$31.00 ©2021 IEEE

A DR model needs to take into account different types of electricity users. There are three main types of consumers in the recent DR models, i.e. residential, commercial and industrial consumers. F. Pallonetto *et. al* implemented various DR algorithms for the residential sector through implementing machine learning models [3]. The effectiveness of this model in the presence of DR is demonstrated in a test-bed in Ireland using two DR algorithms, a rule-based algorithm and a machine learning-based model both under different time-of-use (TOU) tariffs.

Another model in the residential sector of a microgrid is proposed in [4] where a DR program using a hybrid price-based approach which considers uncertainties related to the decision variables. Moreover, there are some models which are more comprehensive from the type of consumers' point of view. For instance, Ref. [5] considered three types of consumers participating in the DR program to make the model more realistic and applicable. In this model, the decision maker's behavior is studied in a risk-taking approach. Information-gap decision theory was used as the measure of risk. The model's main objective was to guarantee that the profit of the aggregator will not be less than a target profit if the uncertain parameter's observed values are in a certain range. To make the proposed model more comprehensive, we use load profiles representing residential, commercial and industrial consumers.

In addition, the DR model is classified into either price-based DR programs or incentive-based DR programs [1]. In incentive-based programs, the participants receive rewards if they reduce their energy usage during peak periods. As an example, Ref. [6] developed a real-time incentive-based DR program considering a combination of a deep neural network and reinforcement learning. Alternatively, price-based DR programs rely on consumers being charged according to various tariffs levels at different periods.

For instance, in Ref. [7], an optimization problem is developed through the modeling a price-based DR program with game theory. The commercial sector is analyzed in this problem. By considering both types of DR programs, the model becomes more flexible. To this end, in this work, the two types of DR programs, price-based and incentive-based, are considered.

Several types of uncertainties could be considered as the uncertain parameter used to analyze the behavior of the optimization models in the DR area. Stochastic programming is an extremely popular method in this area. An optimization model is proposed in Ref. [8] using a risk-averse CVaR approach. Stochastic CVaR strategies are also used to address the uncertainties in a probabilistic manner and considering several aspects of the DR in a microgrid in Ref. [9], [10].

The study of consumer's behavior by considering their load availability is the main novel contribution of this work. This analysis can improve the aggregators trading actions in the wholesale electricity markets with the aim to maximize its profit. To this end, stochastic programming through the CVaR approach is employed in this model to mitigate load risk. Also, load uncertainty is taken into account through the participation factor of the end-users who are enrolled in the DR program through various scenarios.

The rest of the paper is as follows: the problem formulation is given in Section II. Then, Section III demonstrates the experimental results. Finally, the conclusions from the model's main findings presented in the last section.

II. Problem Formulation

Fig. 1 illustrates the proposed stochastic programming model. and according to this figure, in the down-side of the aggregator, there are the residential, commercial and industrial consumers who participate in the DR programs through two programs: incentive-based DR program and TOU program.

The acquired DR could be traded in the day-ahead (DA) market through the aggregator. Energy flows from consumers to the DA market during peak periods and from the DA to consumers in off-peak periods.

In this paper, the load availability is considered as the uncertain parameter and CVaR is chosen as the risk measure to analyze the risk-averse decision-maker's behavior within the wholesale market.

A. Day-Ahead market

In this paper, DR is being traded with the day-ahead (DA) market. Note that the DR aggregator is assumed to participate in electricity markets similar to other market players such as generators, in which they are responsible for their offers.

B. Time-of-Use program

TOU is one of the most popular price-based DR programs. According to this program, each period contains its specific energy usage tariffs that consumers reschedule their energy consumption considering these tariffs.

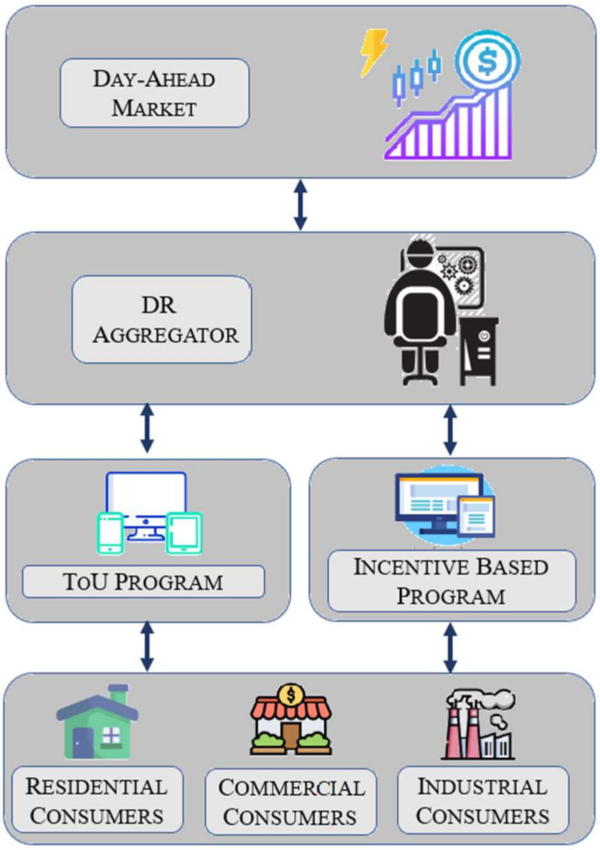

Fig. 1. The traded amount of energy in the DA market.

Elasticity matrix plays an important role in the TOU program, i.e. $E(c,t,p)$. TOU program is modelled through equation (1) as follows:

$$P^{TOU}(t) = \sum_{c=1}^{N} D_0(c,t) \sum_{p=1}^{P} E(c,t,p) \left(\frac{\lambda(c,p) - \lambda_0(c,p)}{\lambda_0(c,p)} \right), \forall t \quad (1)$$

C. Incentive-based DR program

The incentive-based DR program used in this paper is described in the equations (2)-(6). According to these model, amount of DR is cleared in (2) for each hour. $PF(\omega,t)$ indicates scenarios of consumers' participation in this DR program which is a number from 0 to 1. The incentive value is shown in (3) which is limited through (4). Thus, (5) indicates that in each hour, only one step can be chosen by the consumer which explained more in detail in [11].

$$P^{DR}(t) = \sum_{\omega} \pi(\omega). \sum_{j=1}^{N_J} PF(\omega,t). \bar{P}_j^{DR}(t) \,.\, v_j^{DR}(t) \,, \forall t, \forall j \quad (2)$$

$$R^{DR}(t) = \sum_{j=1}^{N_J} R_j^{DR}(t) \,, \forall t, \forall j \quad (3)$$

$$\bar{R}_{(j-1)}^{DR}(t). v_j^{DR}(t) \le R_j^{DR}(t) \le \bar{R}_j^{DR}(t). v_j^{DR}(t), \forall t, \forall j \quad (4)$$

$$\sum_{j=1}^{N_J} v_j^{DR}(t) = 1 \,, \forall t, \forall j \quad (5)$$

$$v_j^{DR}(t) \in \{0,1\} \quad (6)$$

D. The proposed trading model of DR Aggregator

In the problem formulation, the objective function is the maximization of the DR aggregator's profit. The objective function initial term is the revenue from trading DR in the DA market. Thus, the second term refers to the cost that is due to the reward that aggregator has to give to the consumers due to their participation in incentive-based DR program. Finally, the last term indicates the CVaR value. The proposed DR trading framework is presented as follows:

$$Maximize \sum_{t=1}^{T} P^{DA}(t) \lambda^{DA}(t) - \sum_{\omega} \pi(\omega) \sum_{t=1}^{T} \sum_{j=1}^{N_J} PF(\omega,t) \bar{P}_j^{DR}(t) R_j^{DR}(t) + \beta \left(\xi - \frac{1}{1-\rho} \sum_{\omega} \pi(\omega)\, \eta(\omega) \right) \quad (7)$$

subject to:

$$P^{DA}(t) = P^{DR}(t) + P^{TOU}(t) \,, \forall t \quad (8)$$

TOU program constraint (1) (9)

Reward-based program constraints (2) – (6) (10)

$$\xi - \left(\sum_{t=1}^{T} P^{DA}(t) \lambda^{DA}(t) - \sum_{t=1}^{T} \sum_{j=1}^{N_J} PF(\omega,t) \bar{P}_j^{DR}(t) R_j^{DR}(t) \right) \le \eta(\omega) \quad (11)$$

$$\eta(\omega) \ge 0 \quad (12)$$

It should be noted that the risk factor (β) is used as a weighting term for the CVaR calculation. The probability of each scenario ω is indicated by $\pi(\omega)$. The decision variables are P^{DA}, P^{TOU}, P^{DR}. The CVaR calculation also requires two auxiliary variables which are ξ and $\eta(\omega)$. The confidence level of the program is given by ρ that is set at 0.95. Moreover, the risk-factor is utilized as a trade-off between the risk value and the corresponding expected profit. A risk-averse aggregator who seeks to minimize the risk will choose larger values for the risk-factor. Conversely, a more risk-seeking decision-maker tends to select a risk factor closer to 0 to increase profits. Equation (8) represents the balancing constraint of the considered model. The amount of the power traded within the DA market should be equivalent to the DR obtained from the consumers through DR programs at each hour. Constraints (11) and (12) are the CVaR constraints that are necessary for calculating CVaR in the stochastic programming model. As mentioned before, stochastic programming through the use of the CVaR method is proposed to model the uncertainty. The chosen uncertain parameter for the incentive-based program is the load participation factor. Note that it is assumed that the number of scenarios of the participation level of consumers is randomly generated, i.e., $PF(\omega,t)$. Maximizing the aggregator's total profit is the objective of this stochastic problem while satisfying the requirements. This approach is a stochastic strategy for risk-averse decision-makers.

III. Case Study

A. Data Preparation

According to the problem formulation, it is shown that the problem is a mixed-integer linear program (MILP). CPLEX solver is used in GAMS environment to find the optimal solution on a PC with the following calculation specifications: 6 GB RAM and 2.43GHz of CPU speed. It took about 7 seconds to find the optimal solution.

Fig. 2 illustrates the load profiles of consumers. As depicted in this figure, the day can be divided into two periods, i.e., *P=2* considering the electricity consumption pattern, i.e. peak and off-peak. For residential and commercial consumers, the peak period is selected from 09:00 to 22:00 and from 23:00 to 08:00 is considered as off-peak period. However, the load profile for the industrial sector is quite different than in other sectors.

As it is shown in Fig. 2, the peak period starts from 8:00 and ends in 18:00. Therefore, these hours can be chosen as the peak period and from 19:00 to 7:00 is for the off-peak period.

In addition, the trading method is chosen in a way that energy flows from the end-users towards the DA electricity market during peak periods while during the off-peak periods, the energy flow is from the DA market to the end-users.

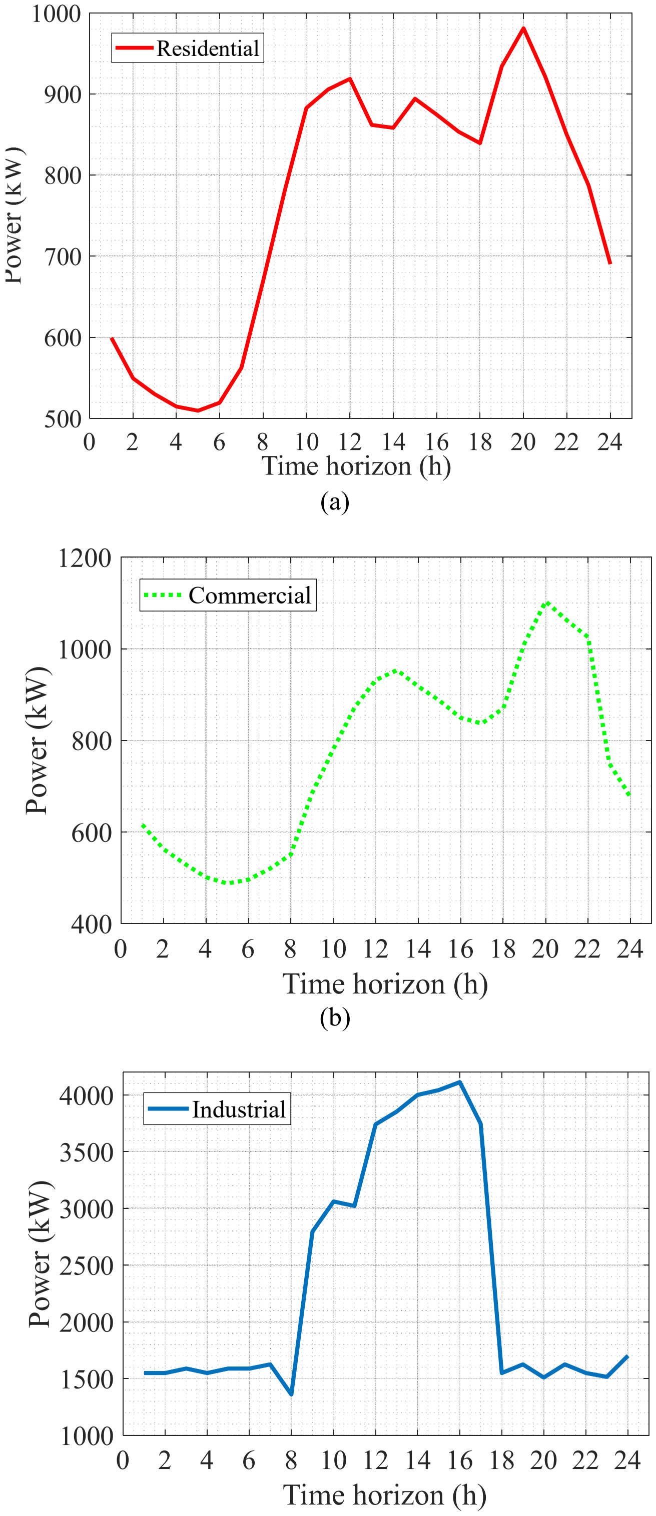

Fig. 2. Daily demand profile of the test system for 24 hours for (a) residential, (b) commercial and (c) industrial consumers.

This means that the aggregator encourages a consumer to decrease their consumption during peak period to trade the required DR in the DA market. Then, motivating them to consume more in the off-peak period. The DR programs that are employed are discussed in the previous section. Table I indicates the elasticity matrix data for the TOU program that is obtained from Ref. [12]. The DA market prices are selected from OMEL for Portugal. The incentive-based DR program contains 25 steps for each sector. Moreover, 20 scenarios are randomly generated to investigate the effects of the consumer's load participation factor in the incentive-based DR program.

B. *Results*

The load uncertainty is accounted for in this model through the participation factor $PF(\omega, t)$ used for the incentive-based DR program. The risk-averse strategy is investigated through stochastic programming. To do this, the results of selected risk factors are illustrated, i.e. β = {0, 0.25, 0.50, 0.75, 1} in Fig. 3. Risk neutral behavior is seen when β =0, and when β =0, the uncertain parameter is not considered. Hence, the results of the model equate the aggregator's profit to be € 203,113.

Fig. 3. shows the calculated values of CVaR for different correlating expected profits. When the CVaR increases, the aggregator becomes more risk-averse and at the same time the expected profit decreases. In other words, the more risk-averse the decision-maker becomes the lower the expected profit becomes. To illustrate more detail of the impact of the stochastic model, two risk factors are considered, i.e. β = {0, 1}. As stated before, β =0 is for the risk-neutral aggregator and as the risk factor increases, the risk-averseness of the program increase as well.

TABLE I: MATRIX OF THE ELASTICITY

		Peak	Off-Peak
Residential	Peak	-0.3	0.1
	Off Peak	0.04	-0.06
Commercial	Peak	-0.32	0.12
	Off Peak	0.06	-0.08
Industrial	Peak	-0.4	0.2
	Off peak	0.14	-0.16

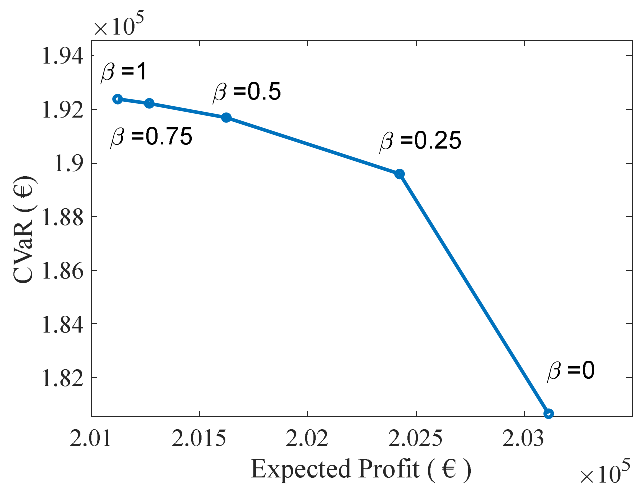

Fig. 3. The expected profit values for different CVaR points.

The behavior after the implementation of the TOU program is illustrated in the subplots of Fig. 4. In Fig. 4(a) the TOU tariffs for the residential and commercial sectors are shown. And (b) depicts the amount of power for the industrial sector. According to this, the results show that during the off-peak period, the demand is increase around 20 kW for the residential and commercial consumers if the TOU program being employed. In the other side, the electricity usage is decreased around 60 kW for residential and 40 kW for the commercial sector if the TOU program is implemented. These values for the industrial sector are 250 kW for the off-peak period and 750 kW for the peak period.

Fig. 5 depicts the reduced amount of energy due to the use of the incentive-based DR program for two cases. For the case of β =0, the amount of DR is higher compared to the amount of energy in the risk-averse mode. The magnitude of this difference is clear when $\beta = 1$ because the risk-averse aggregator is more conservative compared to the risk-neutral one. Since the risk-neutral decision-maker seeks to maximize its profit without consideration of the risk factor.

Fig. 6 shows the DA power profile that the aggregator is going to trade for both the risk-neutral and risk-averse cases. From the figure, the quantity of offered energy in the DA market decreases significantly at 18:00.

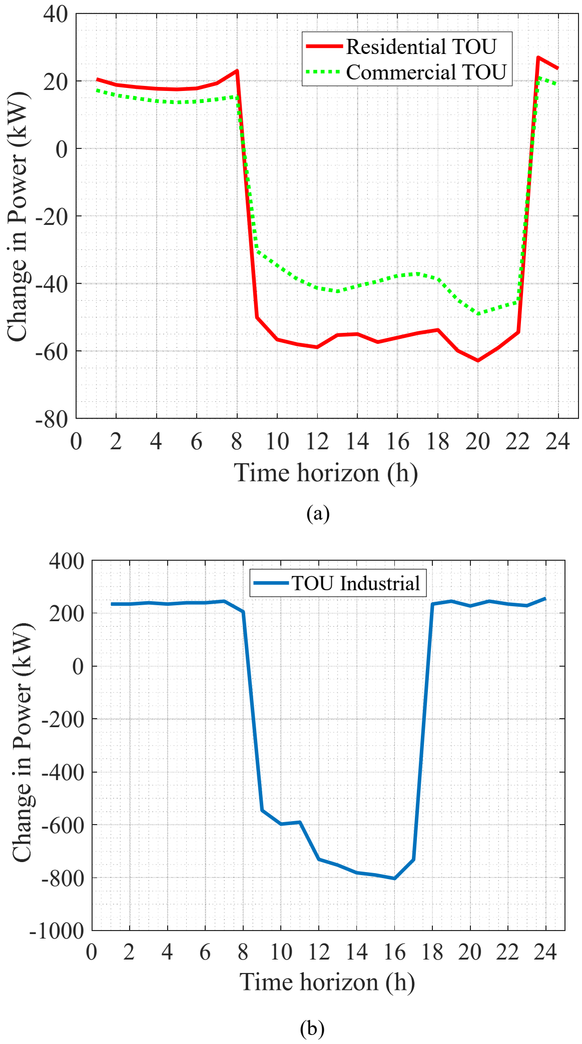

Fig. 4. Results of TOU program implementation.

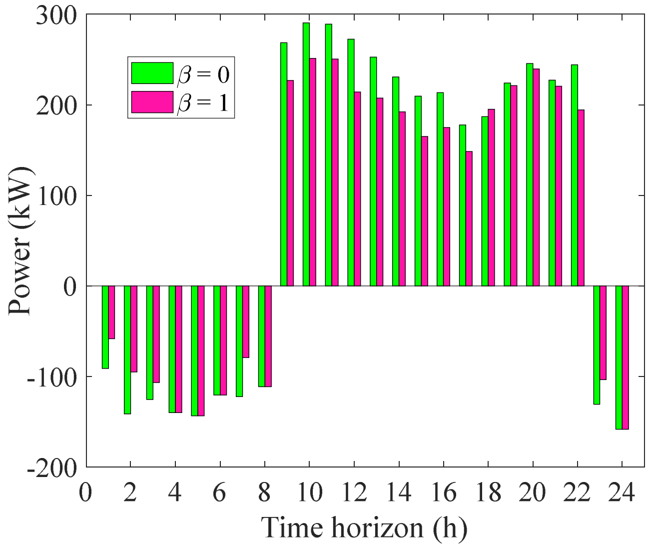

Fig. 5. Reduced amount of energy due to the employment of the reward-based DR program.

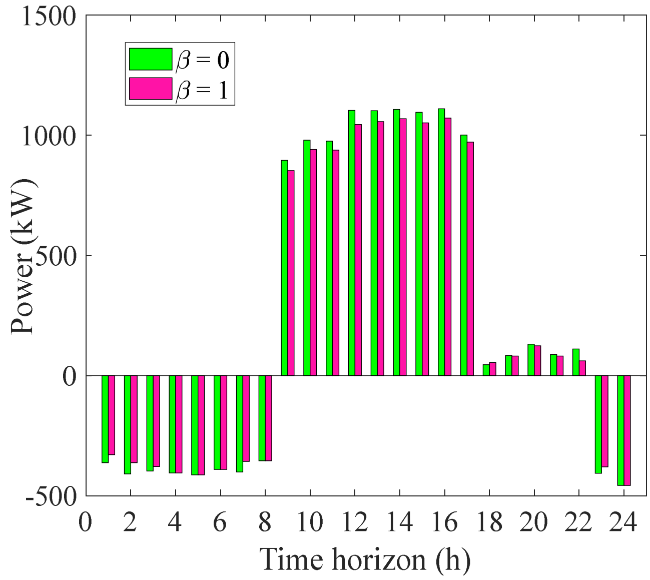

Fig. 6. The traded amount of energy in the DA market.

The main reason for this decrease is the industrial consumers. Since the peak period for the industrial consumers ends at 18:00 the values shown in this figure is the net amount of available DR for the aggregator to be offered in the DA market. This indicates that industrial loads play a major role within the power system and directly affects the DR available.

IV. Conclusions

A risk-averse decision-maker seeks to make its operation more secure against the uncertain parameter. To this end, CVaR stochastic programming is one of the popular approaches to handle the expectations of the risk-averse DR aggregator. Two DR programs in the consumer side have been modeled in this paper and in the energy pool side, DA electricity market was included as well. Load availability was assumed as the uncertain parameter in this model, since the aggregator cannot forecast the exact scheduled DR obtained from the participants due to the uncertain behavior of the consumers in load consumption. The results showed that amount of available DR from the industrial sector is much greater than the residential and commercial sectors. Therefore, the impact of the industrial sector in the optimization problem was higher than the others. Moreover, as the aggregator becomes more risk-averse, results showed that it reduced the amount of energy traded in the day-ahead market, as a safeguard to prevent economic losses. As an extension of this work, reserve markets and balancing markets can also be included in the energy pool to make the wholesale market more comprehensive.

REFERENCES

[1] A. R. Jordehi, "Optimisation of demand response in electric power systems, a review," *Renew. Sustain. Energy Rev.*, vol. 103, pp. 308–319, Apr. 2019, doi: 10.1016/J.RSER.2018.12.054.

[2] M. Vahid-Ghavidel, M. S. Javadi, M. Gough, S. F. Santos, M. Shafie-khah, and J. P. S. Catalão, "Demand Response Programs in Multi-Energy Systems: A Review," *Energies*, vol. 13, no. 17, p. 4332, Aug. 2020, doi: 10.3390/en13174332.

[3] F. Pallonetto, M. De Rosa, F. Milano, and D. P. Finn, "Demand response algorithms for smart-grid ready residential buildings using machine learning models," *Appl. Energy*, vol. 239, pp. 1265–1282, Apr. 2019, doi: 10.1016/j.apenergy.2019.02.020.

[4] H. J. Monfared, A. Ghasemi, A. Loni, and M. Marzband, "A hybrid price-based demand response program for the residential micro-grid," *Energy*, vol. 185, pp. 274–285, Oct. 2019, doi: 10.1016/j.energy.2019.07.045.

[5] M. Vahid-Ghavidel, J. P. S. Catalão, M. Shafie-Khah, S. S. Barhagh, and B. Mohammadi-Ivatloo, "IGDT opportunity method in the trading framework of risk-seeker demand response aggregators," Jun. 2019, doi: 10.1109/PTC.2019.8810601.

[6] R. Lu and S. H. Hong, "Incentive-based demand response for smart grid with reinforcement learning and deep neural network," *Appl. Energy*, vol. 236, pp. 937–949, Feb. 2019, doi: 10.1016/j.apenergy.2018.12.061.

[7] R. Tang, S. Wang, and H. Li, "Game theory based interactive demand side management responding to dynamic pricing in price-based demand response of smart grids," *Appl. Energy*, vol. 250, pp. 118–130, Sep. 2019, doi: 10.1016/j.apenergy.2019.04.177.

[8] M. Vahedipour-Dahraie, H. Rashidizadeh-Kermani, A. Anvari-Moghaddam, and P. Siano, "Risk-averse probabilistic framework for scheduling of virtual power plants considering demand response and uncertainties," *Int. J. Electr. Power Energy Syst.*, vol. 121, p. 106126, Oct. 2020, doi: 10.1016/j.ijepes.2020.106126.

[9] M. Jadidbonab, E. Babaei, and B. Mohammadi-ivatloo, "CVaR-constrained scheduling strategy for smart multi carrier energy hub considering demand response and compressed air energy storage," *Energy*, vol. 174, pp. 1238–1250, May 2019, doi: 10.1016/j.energy.2019.02.048.

[10] Wang, Yang, Tang, Sun, and Zhao, "A Stochastic-CVaR Optimization Model for CCHP Micro-Grid Operation with Consideration of Electricity Market, Wind Power Accommodation and Multiple Demand Response Programs," *Energies*, vol. 12, no. 20, p. 3983, Oct. 2019, doi: 10.3390/en12203983.

[11] M. Vahid-Ghavidel, N. Mahmoudi, and B. Mohammadi-ivatloo, "Self-Scheduling of Demand Response Aggregators in Short-Term Markets Based on Information Gap Decision Theory," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 2115–2126, 2018, doi: 10.1109/TSG.2017.2788890.

[12] A. Hatami, H. Seifi, and M. K. Sheikh-El-Eslami, "A stochastic-based decision-making framework for an electricity retailer: Time-of-use pricing and electricity portfolio optimization," *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 1808–1816, 2011, doi: 10.1109/TPWRS.2010.2095431.