Influence of Demand Response Programs in Microgrids Facing Photovoltaic and Battery Integration

Bruno P. Ramos
Fac. Eng. University of Porto (FEUP)
Porto, Portugal
e-mail: up201504544@edu.fe.up.pt

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

Gerardo J. Osório
Portucalense Univ. Infante D.
Henrique, Porto, Portugal
e-mail: gerardo@upt.pt

Miadreza Shafie-khah
Univ. of Vaasa
Vaasa, Finland
e-mail: mshafiek@univaasa.fi

Ozan Erdinç
Yıldız Technical Univ.
Istanbul, Turkey
e-mail: ozanerdinc@gmail.com

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

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***Abstract*—Yearly, the number of Distributed Energy Resources (DER) integrated into the power grid increases has increased, having a large impact on power generation globally, promoting the introduction of renewable energy resources (RER). To increase the flexibility of the power system with integrated RER, the introduction of energy storage systems (ESS) is essential. Demand response (DR) programs also help to increase grid flexibility, resulting in increased grid reliability as grid congestion and losses decrease. However, this new paradigm shift needs further research and careful analysis. In this work, two types of DR programs are addressed to promote greater participation by different consumers features. To interconnect the different consumers, DR aggregators are inserted to ensure that individual consumers have influence on the power market. All these aspects, if accompanied by information, measurement, communication, and control systems, give rise to the smart grids, playing an essential role. The results show, considering the worst uncertainty case scenario, that there is a suitable total RER of 2151.50 kW, against 3227.30 kW, by not considering the RER uncertainty.**

Keywords-Demand response aggregator; Energy storage; Robust optimization; Smart grid; Solar photovoltaic generation.

I. INTRODUCTION

Climate change is a huge environmental problem that humanity has been fighting against. According to the 2030 Agenda for Sustainable Development of the United Nations (UN) [1], the environmental challenges to be faced are diverse and complex.

The generation of electricity in smaller amounts, closer to end-users and using RER can dramatically increase the energy efficiency, reduce CO_2 emissions, improve the grid resiliency, and reduce the need for new transmission system investments [2]. Because of the characteristic shared among all the renewable sources, their variability introduce uncertainty in the power system, becoming difficult to predict the electricity generation from RER like solar or wind, which happens due to the unpredictability of weather conditions. In the solar photovoltaic (PV) generation case, the variability and unpredictability of generation brings a problem for its integration in the grid.

The PV variability may lead to excess or lack of power generation comparative to the consumer demand. As a result, PV generation installed alone in the grid have a low level of reliability and efficiency [2]. Integrating PV into power grids is a great solution to reduce losses in transmission and distribution cables, to increase resilience in the grid, to lower the costs of power generation, and to reduce the need to invest in new utility to increase the generation capacity [3].

ESS technology led to an evolution of the battery storage along with other storage types but ultimately with a different direction of peak shaving or short-term outage prevention. Nowadays, ESS lead to delay capacity [4], grid expansions [5], frequency and voltage balancing [6], [7], among others. Also, ESS is usually categorized based on their application time-scale, which are referring to the time that it takes between the storage and the use of the energy [8].

This work was developed to solve some challenges that the penetration of RER inflicts in the grid. The main RER that is approached in this work is the solar PV. The work presented in this paper is related to the introduction of PV and ESS, in the consumer side of the grid, and the impacts analysis that the integration will have in the profit of a DR aggregator. The DR aggregator could be implemented in a microgrid to bring together all the DR from the consumer and sell it to the purchaser that can be independent system operators, to participate in the energy market. The model developed has as objective to maximize the DR aggregator profit with the inclusion of PV generation and battery ESS (BESS) at the consumer side. To do that, given a PV generation scenario, the code will reach to the best feasible solution for the DR aggregator of PV-battery-consumer power exchanges interactions and with the purchaser (ISO) maximizing the profit. Furthermore, a study about the PV generation uncertainty considering the robust optimization programming is considered, observing the impacts of the uncertainty of PV generation, which may result of the weather conditions uncertainty or season of the year.

II. PROBLEM FORMULATION

The model developed in this work is composed by three different types of electricity consumers, which are residential, commercial, and industrial.

Each of them is linked to the electricity market using a DR aggregator, which aggregates all consumers demand to sell to the ISO. The consumers can establish contracts with the DR aggregator using two different types of DR programs, such as, reward-based DR programs, which may be an incentive base DR (IBDR) program type or time of use (TOU) program that is a price base DR (PBDR) program type.

Then, the obtained DR aggregated is exchanged with purchasers through the establishment of DR option agreements, or fixed DR contracts. In addition, it is integrated closer to the consumers solar PV generation for self-consumption and with a BESS that may be charged with the excess of PV generation and discharged when the prices of energy are higher, or the PV generation is not enough to supply all demand.

The BESS could also be charged directly with the power bought by consumers to DR aggregator, when the prices of electricity are lower. All these functionalities have as a purpose to maximize the DR aggregator profit and incentive the participation of consumers giving to them an active role on the power system.

In Figure 1, is schematized the behavior and power exchanges for all the system that was modeled. Considering in the bottom block the three consumer types equipped with solar PV generation and BESS. Then, these consumers are aggregated by the DR aggregator using the two types of DR programs, TOU and reward-based DR. Finally, through fixed DR contracts and DR option agreements the DR aggregator link the consumers to the power system.

Such arrangement is used to motivate the consumers to increase their consumption at off-peak periods, and at on-peak periods DR is obtained from consumers, which means that they reduce their consumption and with the introduction of the PV generation and BESS in the consumer side, they could decrease the need to purchase electricity from the aggregator directly using the PV electrical generation with/without the BESS at each time slot.

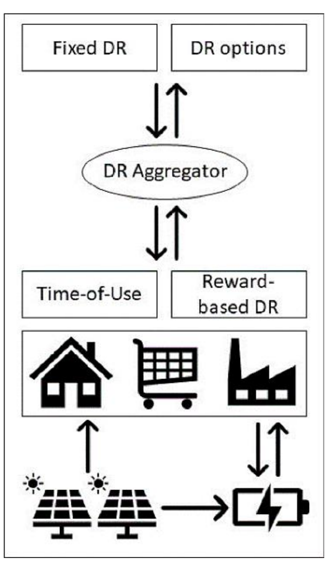

Figure 1. DR aggregator structure with PV generation and BESS system

This code was constructed based on the model for DR aggregator presented [9], considering the solar PV generation and BESS of the consumers, analyzing the impacts that it has on the DR aggregator profit, and the iterations between all the DER that are integrated in this model, PV generation, BESS, DR programs.

Firstly, it is analyzed the behavior of the deterministic optimization model, to observe the impact of the integration of PV generation and battery, on DR aggregator functionality. Finally, it is inserted the uncertainty of PV generation to simulate the uncertain nature, using a robust optimization programming method.

A. Mathematical Formulation

1) Fixed DR contracts

The acquired demand response by the aggregator is traded to the purchaser using the block b of f^{th} contra including the prices $\lambda_{f,b}^{DR}(t)$, DR $P_{f,b}^{DR}(t)$, and DR $(PDR(f\ ;b))$, that is expressed by Equations (1) and (2). The $P(FDR)$ corresponds to the income in dollars for the DR aggregator, resulted from the sale of DR to purchasers that was bought and to the consumers, using DR programs and then aggregated. N_b and N_f are the number of available blocks and contracts respectively.

$$P(FDR) = \sum_{t=1}^{T}\sum_{f=1}^{N_f}\sum_{b=1}^{N_b} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t) \tag{1}$$

$$p_{f,b}^{DR,min} \le p_{f,b}^{DR}(t) \le p_{f,b}^{DR,max} \ , \qquad \forall t \tag{2}$$

2) DR option agreement

After examining the profitability of the DR option chosen for the day, the DR aggregator set an agreement with the purchaser. This agreement can be cancelled but the DR aggregator needs to pay a penalty fee to the purchaser.

This agreement is expressed in Equation (3), where the first term refers to the income for DR aggregator, resulted from the purchase of a DR, specified in the pool of the day at the option chosen by DR aggregator, at every hour $P_{op}^{DR}(t)$, at the correspondent price $\lambda_{op}^{DR}(t)$ specified in the pool of options. The second term is related to the penalty that the DR aggregator must pay to the purchaser if it cancels the agreement.

To see if the agreement is executed or cancelled at every hour of the day, it is used the binary variable $v_{op}^{DR}(t)$, which is 0 if the agreement is cancelled or 1 if it is executed. Equation (4) is a constraint used to limit the value of agreed DR in the DR option agreement.

$$P(ODR) = \sum_{t=1}^{T}\sum_{op=1}^{N_{op}} [P_{op}^{DR}(t).\lambda_{op}^{DR}(t) - \left(1 - v_{op}^{DR}(t)\right).f_{op}^{pen}(t)] \tag{3}$$

$$p_{op}^{DR,min} \le p_{op}^{DR}(t) \le p_{op}^{DR,max} \ , \quad \forall op = 1,2,\dots,N_{op} \tag{4}$$

3) Reward-based DR program

This program is modeled, using Equations (5) to (9). With Equation (5) it is possible to model the reduction of load by the consumers in which PF(t) indicates the participation level of consumers from 0 (unattainable) to 1 (attainable). Equation (6) refers to the donated reward to the consumer for the chosen block at each hour, which is limited by Equation (7). the Equation (8) and (9) certify that the model only chose one reward-based DR step for the load reduction at each hour of the day.

$$P^{DR}(t) = \sum_{j=1}^{N_J} PF(t).\bar{P}_j^{DR}(t).v_j^{DR}(t), \qquad \forall t, \forall j \tag{5}$$

$$R^{DR}(t) = \sum_{j=1}^{N_J} R_j^{DR}(t), \qquad \forall t, \forall j \tag{6}$$

$$\bar{R}_{(j-1)}^{DR}(t).v_j^{DR}(t) \leq R_j^{DR}(t) \leq \bar{R}_j^{DR}(t).v_j^{DR}(t), \quad \forall t, \forall j \tag{7}$$

$$\sum_{j=1}^{N_J} v_j^{DR}(t) = 1, \qquad \forall t, \forall j \tag{8}$$

$$v_j^{DR}(t) \in \{0,1\} \tag{9}$$

4) Time-of-Use program

In TOU programs, the DR aggregator offers different prices to the consumers to possibility the consumer to modify their electricity usage profile according to the offered prices. Elasticity of consumers electricity consumption and, their participation in TOU program is proportional with each other, which means that if the price decrease, more flexible should be the consumer. This program is modeled by Equation (10). The TOU(t) is related to the bill difference resulted from shifting loads by the consumer, which $E(c,t,p)$, refers to the elasticity of the consumer.

$$TOU(t) = \sum_{c=1}^{N} D_0(c,t) \sum_{p=1}^{P} E(c,t,p)\left(\frac{\lambda(c,p)-\lambda_0(c,p)}{\lambda_0(c,p)}\right), \forall t \tag{10}$$

5) Battery energy storage system

For the electrical energy storage system constraints, the Equations (11) and (12), respects to the limitation of the power discharged from the battery and the power charged to the battery at each hour of the day, respectively.

In Equations (13) to (16) is defined the SOC constraints with (13) and (14) defining the initial state of charge of the battery. Equations (15) and (16), respects to the SOC of the battery in the next time slot before one hour charging or discharging, and the SOC value upper and lower limitation, respectively.

$$0 \leq P_{dch}(t) \leq u_{dch}(t) + P_{dch}^{max}, \qquad \forall t \tag{11}$$

$$0 \leq P_{ch}(t) \leq u_{ch}(t) + P_{ch}^{max}, \qquad \forall t \tag{12}$$

$$a.SOC^{max} = SOC(t = T_{final}) \tag{13}$$

$$SOC^{initial} = a.SOC^{max} \tag{14}$$

$$SOC(t) = SOC(t-1) + P_{ch}(t).\eta^{ch} - \frac{P_{dch}}{\eta^{dch}} \geq 1 \tag{15}$$

$$SOC^{min} \leq SOC(t) \leq SOC^{max}, \qquad \forall t \tag{16}$$

$$0 \leq u_{dch} + u_{ch} \leq 1, \qquad \forall t \tag{17}$$

6) PV generation

The next three Equations, (18) to (20), are for the PV generation array. The PV array upper and lower limitation is in Equation (18). The two Equations, (19) and (20), refers to the minimum and maximum values that the PV generation in each time slot may have for the robust optimization problem.

$$P_{pv}^{min}(t) \leq P_{pv}(t) \leq P_{pv}^{max}(t), \qquad \forall t \tag{18}$$

$$P_{pv}^{min}(t) = P_{pv}^{avg}(t).(1-\alpha), \qquad \alpha \in [0,1], \forall t \tag{19}$$

$$P_{pv}^{max}(t) = P_{pv}^{avg}(t).(1+\alpha), \qquad \alpha \in [0,1], \forall t \tag{20}$$

7) Robust Optimization Programming Model

The next equations are relative to the robust optimization programming model formulation for the solar PV generation uncertainty. Due to the fact this is a maximization problem of the DR aggregator profit, for the formulation of the RO model it is necessary to minimize the total PV generation of the day according to the budget of uncertainty value Γ, defined as an integer parameter, which value may fluctuate between 0 and T (total number of time slots considered), which in this case $T = 24$.

If $\Gamma = 0$, it is the same that ignoring the effect of the uncertainty parameter and we obtain the results for the deterministic model considering the $P_{pv}^{max}(t)$ in all time slots, resulting in the best-case scenario for the DR aggregator profit maximization. If it is considering the $\Gamma = T$, it is the same that consider the PV generation uncertainty in all time slots, resulting in the worst-case scenario for the DR aggregator, so it turns the minimum value of profit maximization possible. The uncertainty interval for $P_{pv}(t)$ is defined in Equations (18) to (20). Considering a percentage of the average PV generation of 20 scenarios of production. To obtain the Equations (21) to (28), it is considered 2 dual variables $\xi(t)$ and β which are inserted in the Equation (21) with negative signs. This happens to insert the PV uncertainty parameter in the balance equation of the maximization model (30). Changing the signal, it is possible to just maximize the profit, maximizing the total PV generation deviation, minimizing the PV generation at the same time respecting the considered Γ value.

Equation (21) is calculating the total PV generation of a day considering the uncertainty budget. For each hour the RO is using the maximum PV generation. If $\Gamma = 0$ and knowing that this problem is a maximization problem, maximizing the profit of DR aggregator the model is considering the best-case scenario for the PV generation where at every hour the generation is maximum.

Increasing the Γ, the model is considering the worst-case scenarios of production for the number of time slots equal to Γ, so the problem became a Max-Min type. To solve that, and to transform this into a maximization type problem, it is added two dual variables that are limited in Equations (23) to (25).

$$P_{pv}^{Total} = \sum_{t=1}^{T} \left[P_{pv}^{max}(t).x(t) - \xi(t) \right] - \Gamma.\beta, \qquad \forall t \qquad (21)$$

$$P_{pv}^{Total} = \sum_{t=1}^{T} P_{pv}(t), \qquad \forall t \qquad (22)$$

$$\beta + \xi(t) \geq \left(P_{pv}^{max}(t) - P_{pv}^{min}(t) \right).y(t), \qquad \forall t \qquad (23)$$

$$\xi(t) \geq 0, \qquad \forall t \qquad (24)$$

$$\beta \geq 0 \qquad (25)$$

$$y(t) \geq 0, \qquad \forall t \qquad (26)$$

$$x(t) \leq y(t), \qquad \forall t \qquad (27)$$

$$x(t) \in \{0,1\}, \qquad \forall t \qquad (28)$$

8) Objective function

Equation (29) is the objective function (OF) of the model, it is responsible to maximize the profit of the DR aggregator. The first term of the OF obtain the income from selling DR with fixed DR contracts to the purchasers. The second term the income of selling DR using DR option agreements to the purchasers followed by the penalty fees if the DR aggregator cancels that agreement.

The last term represents the rewards that the DR aggregator needs to pay to the consumers that assign to the reward-based DR four their load reduction. Maximizing the OF is the same that maximizing the PV generation, the model is minimizing the PV generation while the objective function is being maximized because of the inserted constraints of the RO model.

Furthermore, Equation (30) represents the energy balance of the system between the demand and supply of energy. In this equation, is integrated the power charged and discharged of the BESS and the solar PV generation at each hour considering the uncertain nature of this RER, using the robust optimization (RO). The first and second terms of Equation (30) are related to the DR traded by the DR aggregator with the purchaser using DR fixed contracts and DR option agreements, respectively. The third term is related to the DR traded by the consumer with the DR aggregator using reward-based DR program.

The fourth, is the load difference resulted from the use of TOU program at each hour. The fifth and sixth terms are related to the power that is used to charge and the power that is discharged of the BESS at each hour of the day. Finally, the last term is related to the PV production at each hour of the day, and it can be considering uncertainty if in the RO programming model, the budget of uncertainty upper than zero or not if this budget of uncertainty is equal to zero.

The following constraints are related to all the variables that are inserted in the OF and in the balance equation. In addition to the balance constraint, to the objective function equation is added as constraints associated to Fixed DR contract Equation (2), that is associated to Fixed DR contracts.

Equation (4), associated to DR option agreements. Equation (5), associated to TOU program. Equations (6) to (10), associated to the reward-based DR program. Equations (11) to (17) associated to the BESS. Equations (18) to (20), associated to the PV generation model. Equations (21)-(28), associated to the robust optimization programming method.

$$\begin{aligned} Max\ B = \sum_{t=1}^{T} \Bigg[& \sum_{f=1}^{N_f} \sum_{b=1}^{N_b} \left[P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t) \right] \\ & + \sum_{op=1}^{N_{op}} \Big[P_{op}^{DR}(t).\lambda_{op}^{DR}(t) \\ & - \left(1 - v_{op}^{DR}(t) \right).f_{op}^{pen}(t) \Big] \\ & - \sum_{j=1}^{N_j} PF(t).\overline{P}_j^{DR}(t).R_j^{DR}(t) \Bigg] \end{aligned} \qquad (29)$$

$$\begin{aligned} \sum_{f=1}^{N_f} \sum_{b=1}^{N_b} P_{f,b}^{DR}(t) + & \sum_{op=1}^{N_{op}} P_{op}^{DR}(t) \\ & = P^{DR}(t) - TOU(t) - P_{ch}(t) \\ & + P_{dch}(t) - P_{pv}(t), \quad \forall t \end{aligned} \qquad (30)$$

III. Case Study and Results

The proposed program is formulated as a mixed integer linear program (MILP) and was used the CPLEX solver under General Algebraic Modeling System (GAMS) to obtain the results. To study the proposed model, different values of uncertainty budget was inserted to the RO model, to simulate the PV generation uncertainty of the PV-battery system. For this model is considered two distinctive time periods of a day, the on-peak period, which is considered from 9:00 am until 10:00 pm and the off-peak period are the remaining hours of the day. In addition, in this model are considered three different types of consumers, which are residential, commercial, and industrial, each one with different characteristics of consumption. Furthermore, for the PV array, was imported 20 scenarios of PV production from Belgium measures and up scaled values using the website [10].

Then, the average of all 20 scenarios of generation resulted the p.u. values of a possible scenario of production dividing the PV array average for the maximum nominal capacity of PV generation of the forecast values. The DR is being bought from the consumers by the DR aggregator and then it is being sold to the purchasers by the aggregator during the on-peak hours and during the off-peak periods the DR is by the customers to the DR aggregator and then it sells again to the consumer the DR.

TOU prices for each consumer are derived from retail tariffs from reference [11]. The data for reward-based DR programs was extracted from [12]. For PV generation in deterministic model the values were obtained from extracting 20 case production scenarios, measured and upscaled. Then those profiles were used considering 500 kW installed PV generation on the consumer side. For the robust optimization model, it is considered that the budget of uncertainty can takes value from 0 to 24 (Γ). It is also defined that the minimum PV generation is 80% of the average PV generation that was obtained from 20 scenarios of generation and the maximum PV generation possible is 120% of that PV average.

It is possible to find out that, when $\Gamma = 0$, is considered a deterministic resolution of the model using the maximum PV generation for the PV array so in this situation, the profit is maximum with a value of 311.7 thousand of dollar. Hence, when it is considered $\Gamma = 24$, the profit is the minimum possible, with a value of 278.3 thousand of dollar, this is due to consider the PV minimum values for every hour of the day, being the worst situation possible. The DR aggregator is ranging from 278.3 to 311.7 thousand of dollar considering the uncertainty of PV generation. Analyzing the Figure 2, between $\Gamma = 0$ and $\Gamma = 12$ approximately, the profit reduction is reversely linear with uncertainty. After $\Gamma = 12$, the profit starts to be a constant distribution. This occurs because of the RO program start to introduce the uncertainty in the hours when the sun radiation is lower so, increasing the budget of uncertainty, the deviation of profit turns smaller.

The model minimizes the PV generation in the hours that has more generation minimizing the daily PV generation, maximizing the profit. Increasing the budget of uncertainty, the RO programming method starts to act in the hours when the PV generation is low because of the small or none amount of sun radiation. Because of that the deviation of the profit at high values of uncertainty is getting smaller and smaller until being zero. Observing the PV generation array for the 24 hours of the day, using different values of uncertainty budget, it is possible to verify that when $\Gamma = 0$ it is considered deterministic model values for the PV generation, so the PV generation uncertainty is not considered. Increasing the Γ is the same to increase the uncertainty on the PV generation. In Figure 3 that the RO model starts to minimize the time slots of the day when the sun radiation is higher, around the mid of the day, minimizing the total PV generation of the day considering the budget of uncertainty chosen. Increasing the uncertainty budget value, the total PV generation decrease.

Increasing the uncertainty budget value, the total PV generation decrease. In Table I are the values of total PV generation for one day and is possible to see that these values decrease with the increase of uncertainty. The BESS is used to charge the excess of supply using in the future, improving the flexibility of the consumers. In Figure 4, is shown that the state of charge (SOC) of the BESS increase over the first hours of the day, this is a result of the off-peak period in those hours so, the battery is only charged, which is verified by Figure 5.

The battery discharges a total of 112.83 kW and charge a total of 165.90 kW for a value of $\Gamma = 0$. For $\Gamma = 7$, the battery discharge 105.30 kW and is charged 154.90 kW.

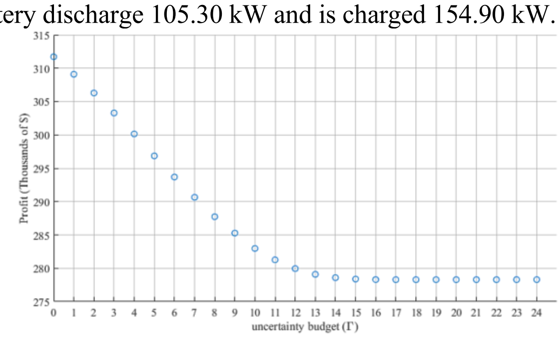

Figure 2. Profit of DR aggregator considering the PV generation uncertainty budget.

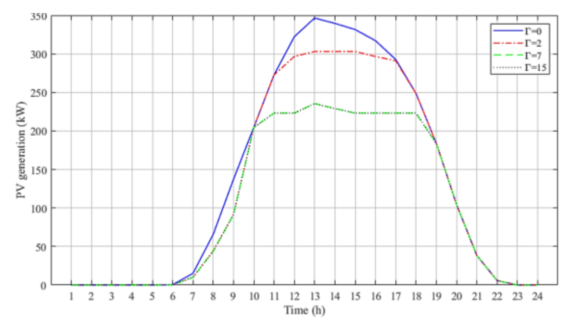

Figure 3. PV generation for different values of uncertainty Γ for all time slots of one day.

TABLE I: PV GENERATION FOR AN ENTIRE DAY USING DIFFERENT Γ VALUES

Uncertainty budget (Γ)	Total PV generation (kW)
0	3227.30
2	2998.60
7	2486.40
15	2153.70
24	2151.50

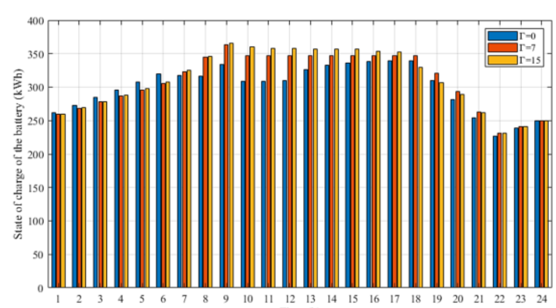

Figure 4. Energy stacked in the BESS for each time slot with Γ.

Also, for $\Gamma = 15$, the battery discharge 107.80 kW and is charged with 158.5 kW. Comparing both cases the charged power increase when $\Gamma = 15$ due to higher load reduction of the consumer resulted from the decrease of PV generation d when the uncertainty increases. The behavior of time-of-use program implemented is in Figure 6 It is possible to observe that at on peak periods the difference between the initial demand and the demand after applied the TOU tariffs is positive, so the DR aggregator is increasing the supply to consumers in 117.9 kW per hour. At on peak period, the consumer is decreasing the demand in 335.9 kW per hour.

In Figure 7 is represented the results for the reward-based DR program of the load reduction of the consumers at each hour and for different values of budget uncertainty. During the off-peak period, the values of increased load to compensate the decrease at the on peak period are the same for all hours and Γ. At on peak period, with the increase of PV generation the load reduction decreases, and the opposite happens.

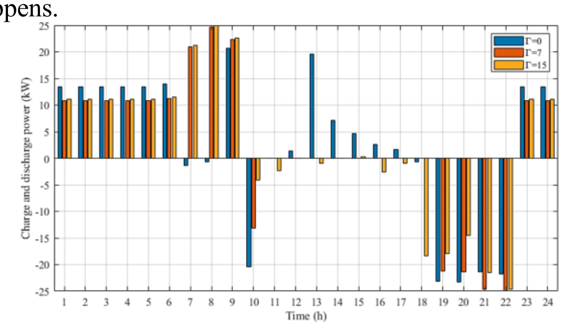

Figure 5. Charge and Discharge power in kW for all time slots with different Γ, in the BESS.

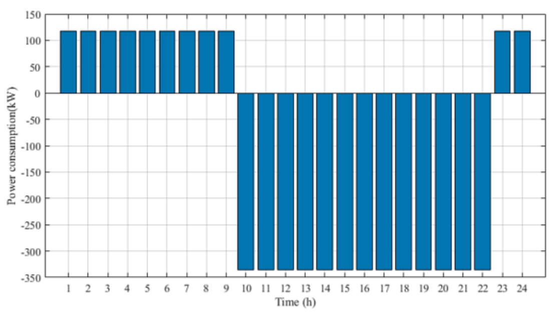

Figure 6. Time-of-use program results in kW.

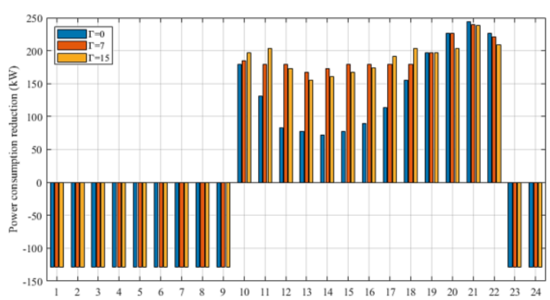

Figure 7. Load power reduction by consumers in kW, for reward-based program for several Γ.

IV. CONCLUSION

The addition of ESS and DR programs to the solar PV generation is essential to overcome the uncertain nature of PV, improving the flexibility of the power system in terms of demand by the consumers and supply by the PV-battery system. It was possible to observe when the uncertainty from PV generation was not considered, it reached the maximum generation of 3227.30 kW, which decreased as expected when the uncertainty parameter Γ was considered, the worst-case PV uncertainty scenario from PV with 2151.50 kW.

The integration of DR programs through aggregators motivates the participation of the consumers in DR programs, contributing to the decentralization of the power system, promoting an active role to the consumer in the grid and electricity energy markets, where their consumptions profiles will impact the price of electricity. Hence, the application of this work in a power market was to understand how the consumers energy behavior would affect the price of electricity. Introducing the participation uncertainty of the consumers in DR programs would be an interesting theme for a future work. Also for future work, the integration of other sources of RER, such as wind together with the uncertainty of generation could be implemented.

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