A NOVEL OPTIMAL ELECTRICITY PRICING METHOD IN MICROGRIDS BASED ON CUSTOMERS' PARTICIPATION LEVELS

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ABSTRACT

The main focus of this paper is to determine floating smart tariffs for customers in a microgrid via the optimal energy scheduling and combination of PV system size and battery capacity. For a higher return on investment, increasing customers' income and MGOs' profits a novel smart tariff policy is presented. An optimization problem was formulated which resulted in a mixed integer linear programming (MILP). To verify the algorithm it's evaluated on a microgrid with 850 DR-enabled customers. The simulation results show significant end-users' bill decrement and also Peak and PAR index reduction for the aggregate load.

INTRODUCTION

Demand response is a way of associating customers to other grid entities. If the customers are properly motivated with incentives such as smart tariffs, its benefits will cover all of the grid. Many literatures are based on defining a tariff policy to satisfy customers, operators, retailers or both or all of them. For example, Authors in [1] present an overview of residential DR systems, load-scheduling methods and relevant information and communication technologies on smart DR systems. In [2], Schreiber et al review several tariff policies for residential microgrids which all serve the same layout and price net generation at a fixed flat rate. The study in [3] has evaluated differences between feed in tariff, net metering, and net purchase and sale that each framework has been characterized by microeconomic modelling. Several papers such as [4,5] deal with examining demand charges with seasonal variation that cost the highest net load peak. Meanwhile unlike demand charges, in [6] so-called capacity charges are evaluated which only cost net load peaks and apply to the highest absolute of them. Also, [7] Indicates impacts of different tariff structures on the consumers.
With regards to the mentioned studies, we decided to present a new scheme of tariffing which fits to each customer. Consequently, our paper deals with a new scheme of the tariff policies which depends on customers' participation levels in demand response programs. To the best of our knowledge, the presented method in this paper is novel because of its goal functions and policies. A smart tariff motivates customers to do response. So in this paper, we solve this subject by customers themselves.

DISTRIBUTED SMART TARIFFING

A novel tariff policy based on level of customers' participation in DR programs is considered. The advantages of this mechanism is for both sides, operator and customers. Operator finds the ability of loads control and costumers face lower bills. In our model, it is assumed the customers are microgrid-connected and equipped with PV Systems and electricity storages to meet the load demand in all time slots. The customers are equipped with smart meter that can communicate with other users or the microgrid central operator via two-way communication system. They are also supposed to be price anticipating and trying to maximize their payoff by optimal resource utilization of the local generation and storage capacity as well as contributing in DR programs. In what follows, the model of the microgrid and the customer sides will be presented. In the proposed mechanism, the microgrid operator submits different bids to the costumers based on their contribution level during DR hours. Therefore, the electricity rate in the mentioned bidding scheme is:

$$\pi_i^0 = \frac{YBill_i^{opt} - YBill_i^0}{\sum_{t0=1}^{YDRH} DR_i^{t0}} \quad (1)$$

Where π_i^0 is the tariff during DR periods, $YBill_i^{opt}$ is the solution of the main optimization problem (1) and $YBill_i^0$ are the yearly bills for customer i without carrying out the optimization. $YDRH$ is the sum of DR hours in a year. DR_i^{t0} is the customer i's load demand in time $t0$. Eq 1. Implies that the electricity rates during peak times is inversely proportional to different customers' committed load reductions. It is assumed that all customers are price anticipating. That is, they know that the electricity price is calculated according to (5), consequently they are automatically motivated to increase their participation in the proposed DR program. Tariffs are set somehow to compensate customers' incurred cost for installing and maintaining local electricity generations and storages which are needed to participate in the proposed demand response program. This novel theory provides a framework developing a proper optimal energy scheduling. The objective aims at minimizing the total annual cost for a customer and formulated as below:

$$J_i = N_{pv,i} \times AnnualCost_{pv} + N_{ES,i} \times AnnualCost_{ES} + \sum_{day=1}^{365}\sum_{h=1}^{24}\left(E_{h,day,i}^{buy}.\pi_{h,day,i}^{buy} - E_{h,day,i}^{sell}.\pi_{h,day,i}^{sell}\right) \quad (2)$$

$$\underset{E_{h,day,i}^{buy},E_{h,day,i}^{sell},N_{pv,i},N_{ES,i}}{\text{minimize}} \quad J_i \tag{3}$$

Where h denotes the sampling time (hour). $N_{pv,i}$ and $N_{ES,i}$ are the numbers of a typical 250Wp solar panel and 24V12AH battery for customer i respectively. Likewise, $AnnualCost_{pv}$ and $AnnualCost_{ES}$ are equivalent annual cost. For customer i, $E_{h,day,i}^{buy}$ and $E_{h,day,i}^{sell}$ are the amount of buying/selling electricity in hour 'h' on day 'day' respectively, likewise $\pi_{h,day,i}^{buy}$ and $\pi_{h,day,i}^{sell}$are hourly buy/sell price. The optimization model (2) has the following constraints:
According to the customers' power purchase or sell agreements or technical limitations, the amount of power purchased $P_{h,day,i}^{buy}$ or sold $P_{h,day,i}^{sell}$ should not exceed the maximum values $demand_{h,day,i}^{buy}$ and $demand_{h,day,i}^{sell}$ respectively. They're considered in Eq. 4-5.

$$\forall\{h, day\}: 0 \le P_{h,day,i}^{buy} \le demand_{h,day,i}^{buy} \tag{4}$$

$$\forall\{h, day\}: 0 \le P_{h,day,i}^{sell} \le demand_{h,day,i}^{sell} \tag{5}$$

Eq. 6-7 reflecting the state of charge (SOC) for the batteries and sets the limit that they should not be charged and discharged simultaneously.

$$SOC[h+1] = SOC[h] + (1-\zeta_{\mathrm{ch}}).E_{h,day,i}^{ch} - (1+\zeta_{\mathrm{dch}}).E_{h,day,i}^{dch} \tag{6}$$

$$P_{h,day,i}^{ch} \times P_{h,day,i}^{dch} = 0 \tag{7}$$

Due to inefficiency a portion $\zeta_{\mathrm{ch}}\ or\ \zeta_{\mathrm{dch}}$ of the Energy is typically loss; then the energy effectively stored is$(1-\zeta_{\mathrm{ch}}).E_{h,day,i}^{ch}$, while the released one needed to guarantee a power supply $P_{h,day,i}^{ch}$ is $(1+\zeta_{\mathrm{dch}})E_{h,day,i}^{dch}$. The power balance considering the possible PV generation $P_{h,day,i}^{pv}$ and storage charge $P_{h,day,i}^{ch}$ and discharge power $P_{h,day,i}^{dch}$, load power consumption $P_{h,day,i}^{load}$ to fulfill the energy demand is:

$$P_{h,day,i}^{buy} - P_{h,day,i}^{sell} + P_{h,day,i}^{pv} - P_{h,day,i}^{ch} + P_{h,day,i}^{dch} - P_{h,day,i}^{load} = 0 \tag{8}$$

The stored energy in batteries should be between the minimum (DOD) and maximum SOC_{max} (9); allowable limits in accordance with the technical specifications that leads to increasing the lifetime of batteries and avoiding deep discharging or over-charging events.

$$\forall h:\ \ DOD \le SOC(h) \le SOC_{max} \tag{9}$$

Eq. 10 notes the amount of the $SOC(end)$, stored energy in batteries at the end of scheduling should be greater than a minimum customer's desirable value $SOC_{desired}$.

$$SOC_{desired} \le SOC(end) \tag{10}$$

The maximum of the PV size $N_{pv,i,max}$ is also dependent on the available installation area A_{PV} such as possible spaces in the yard or rooftop of a building that affects the optimization results. It's a limit which is shown in Eq. 11.

$$N_{pv,i} \le N_{pv,i,max} \propto A_{PV}(m^2) \tag{11}$$

Economic assessment of PVs and Storages based on the life cycle should be performed. It is done by calculating the average total cost to build and operate a power-generating or a Storage asset over its lifetime.so, the equivalent annual cost (AEC) of PVs and storages is the cost per year of owning and operating them over their entire lifespan which are formulated as below:

$$AnnualCost_{PV\ or\ ES} = \frac{NPV_{PV\ or\ ES}}{A_{ny,r}} \tag{12}$$

$$A_{ny,r} = \frac{1 - \frac{1}{(1+r)^{ny}}}{r} \tag{13}$$

Where r the annual interest rate and ny is the number of years lifespan. NPV is extracted from the net present value calculation of PVs and ESs.

MICROGRID OPERATOR'S BENEFITS:

Postponing future investments in the grid, increasing reliability, reducing total energy loss and Carbon footprint is are the benefits' samples. Apart from these concepts, as the peak demand times often correspond with the highest prices, In this study we model the effect of peak reduction $Ener_{Reduc}$ on MGOs' economic benefits MGO_{Ben} by 3 parameters: reliability enhancement $Reli_{ben}$ Loss reduction LR_{ben} and postponing additional investments $\mathrm{PIn}_{\mathrm{ben}}$. The mentioned equation is as below:

$$MGO_{Ben\left(\frac{\$}{year}\right)} = Reli_{ben} + LR_{ben} + PostIn_{ben} \tag{14}$$

Where:

$$Reli_{ben\left(\frac{\$}{year}\right)} = Reli_{save\left(\frac{\$}{kWh}\right)} \times Ener_{Reduc\left(\frac{kWh}{year}\right)} \tag{15}$$

$$LR_{ben\left(\frac{\$}{year}\right)} = LR_{save\left(\frac{\$}{kWh}\right)} \times Ener_{Reduc\left(\frac{kWh}{year}\right)} \tag{16}$$

$$PIn_{ben\left(\frac{\$}{year}\right)} = PIn_{save\left(\frac{\$}{kWh}\right)} \times Ener_{Reduc\left(\frac{kWh}{year}\right)} \tag{17}$$

These parameters should be derived from statistical studies for a specific microgrid that depend on many things including the upstream rates, number of customers, usage profiles, load factors, the grid structure, the equipment health status, values of reliability indices, Possibility to service new subscribers and etc.

PERFORMANCE EVALUATION

In this section, the performance of the proposed algorithm is evaluated to show the efficiency of the proposed model. Consider a microgrid system with 850 customers who have accepted to participate in the tariffing program. They are classified in 5 categories based on their participation level (different power reduction levels) in DR program. The day is divided to 24 one-hour time slots. Specifications of this case study are listed in Table 1. The customers are grid-connected and also supplied by local PVs and Batteries. Simulation was carried out and results show significant peak demand reduction in the participation hour times as well as saving in yearly cost for customers which are also presented in Table 2. Also, in Table 3 the MGO's benefits by implementing the method for all categories are presented. This fact also shows the MGO side's individual rationality of the proposed smart policy. Fig. 1 illustrates consumption curves for different customers in category 1 on a specific day, with and without applying this method. As it derived from Fig. 1 by applying the proposed algorithm, peak shaving is achieved and PAR index decreases. Fig. 2 Illustrates Throughout the peak hours more energy from batteries is released to avoid exceeding criteria of the DR program.

Algorithm convergence

In real-world, the scheduling algorithm should be deployed for a large number of customers. Therefore, the running time of the algorithm is an important factor to evaluate its efficiency. To show the computational complexity of the algorithm, the running time with respect to the number of customers in category 3 on a specific day are given in Table 4. It can be seen that even for a large number of the customers, the running time is acceptable. As a result, it is concluded that the proposed algorithm can be implemented in scenarios with large number of customers.

CONCLUSION

The present paper offers a novel smart tariff policy which is computationally tractable to motivate customers do response in the proposed DR program. The challenge is how much is the optimal investing in local generation and storages for customers with regards to electricity rates. By applying the proposed scheme expected benefits taking into account particularly customers and MGOs are achieved. Simulation results have shown that the proposed algorithm can perfectly determine floating electricity rates of the peak periods and converges fast even for large number of customers. Furthermore, it has been demonstrated that the proposed approach reduce the customers' bill and the PAR index for the aggregate load by optimal energy scheduling of the microgrid's end users. Because of the significant cost saving of this program each customer aims to locally increase its participation level. The MGO's profit are also increased after applying the proposed smart tariffing. Consequently, it can be concluded that the proposed policy not only grants sufficient flexibility to the MGO, but also assists customers to manage their electricity consumption, PVs and storages allocation wisely in order to reduce their yearly cost.

Table 1.The case study specifications

Category	Number of customers	Amount of power reduction during DR program hours (kW per costumer)	Tariff($cent/kWh)			
			[00:00 08:00]	[08:00 17:00]	[17:00 24:00]	
					With DR	W/O DR
1	350	0.5	6	10	12.9	16
2	180	1	6	10	12.8	16
3	220	1.5	6	10	12.7	16
4	60	2	6	10	12.6	16
5	40	2.5	6	10	12.5	16

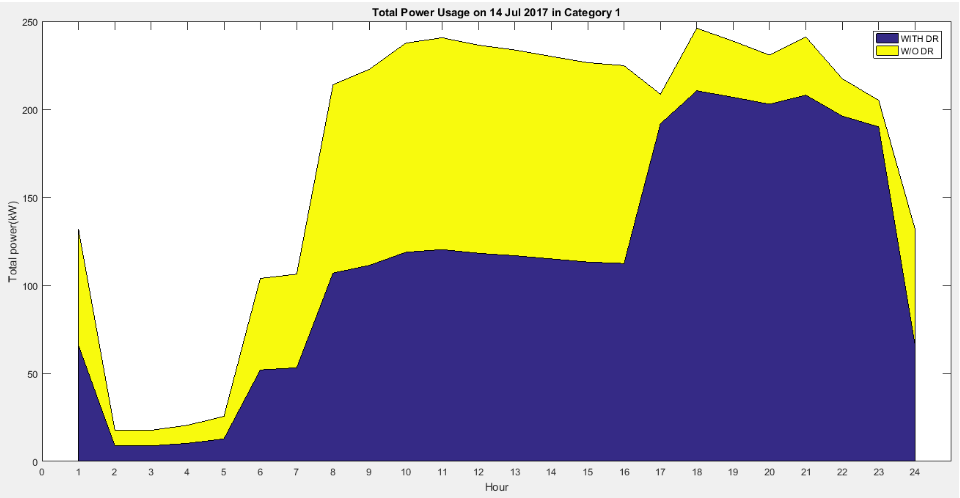

FIG1.Total power usage on 14 Jul 2017 in category 1

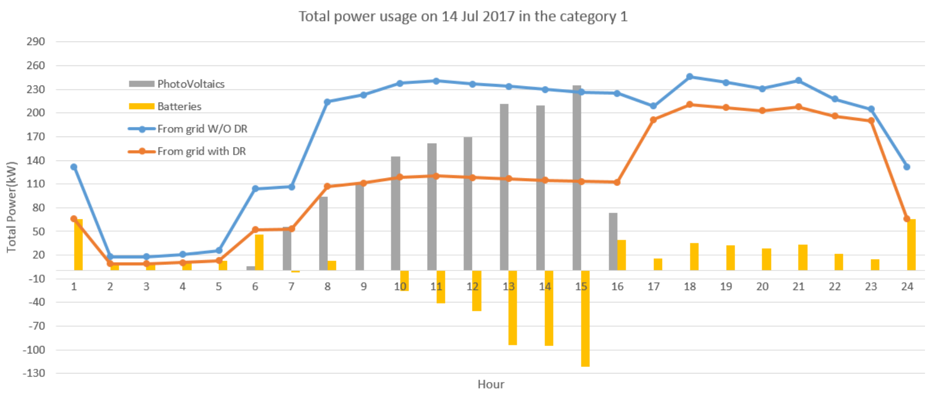

FIG2. Separated Power values on 14 Jul 2017 in the category 1

Table 2.The Simulation results

Category	Total Peak Load In instant t0 (kW)		A sample customer's			
			Yearly Electricity Bill ($)			Yearly cost of enabling PVs and batteries($)
	W/O DR	With DR	W/O DR	WITH DR	DIFF	
1	210.5	120.3	208.3	143.4	64.9	64.8
2	215.3	153.0	254.1	178.8	75.3	75.2
3	390.5	165.6	334.2	245.7	88.5	88.1
4	168.7	155.2	373.9	273.5	100.4	100.2
5	204.1	127.4	392.1	284.0	108.1	108.0

Table 3.The MGO's benefits results

	MGO Yearly economic benefit($) from			
	Reliability enhancement	Postponing the Investments	Power loss reduction	Sum of the benefits($)
1	986	788	1643	3416
2	1115	892	1858	3865
3	1982	1586	3304	6872
4	698	559	1164	2421
5	526	420	876	1822
Total	5307	4245	8844	18397

Table 4.Running time for the proposed algorithm

Number of customers	Running time (in sec)
100	5.31
200	9.12
300	21.41
400	39.73
500	149.17
1000	286.85

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