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Economical Analysis of Flexibility in Micro Grids

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Abstract: As energy demand increased and production means diversified, conventional approaches of looking into distribution grids need to evolve. The Smart Grid paradigm introduces new possibilities of real-time market sensing and interaction models between producers and consumers. In particular, by understanding the types of consumers and their potential willingness to adapt their energy demand with price incentives, innovative pricing strategies in the Smart Grid are expected to lead to better production management, profit maximization and end consumers satisfaction levels. In this work we propose a novel framework and a simulation scenario of a global energy network with heterogeneous types of producers and consumers from which different types of behaviors and interactions can be studied.

1 INTRODUCTION

As energy demand increased and production diversified, conventional approaches of looking into distribution grids needed to change. The overarching goal being to equilibrate an (up until now) non-controllable consumption with a volatile and partly non-controllable production, there is a strong need to understand, model and interact with consumers. The smart grid paradigm emerged from these considerations. It is a communication network coupled to the electricity one, allowing real-time information exchanges (and thus interactions) between energy producers and consumers.

The formulation for the smart grid was aided by the works of (Albadi and El-Saadany, 2007). Further improvement were made in (Chen et al., 2011) and (Mohsenian-Rad et al., 2010a), where attempts were done to schedule the needs of the consumers in response to the tariff announced by the electricity provider. (Momoh et al., 2009) talked about developing the tools to bring the concept into reality. The economics analysis of smart grids took a new direction with the application of game theory as pointed out by (Maity and Rao, 2010) who proposed competing pricing mechanism for markets involved in the smart grid model based on the auction theory. (Fadlullah et al., 2011), (Mohsenian-Rad et al., 2010b), (Saad et al., 2012), (Nguyen et al., 2013) studied strategies from the consumer and producer point of view to increase their revenues. (Gkatzikis et al., 2013) proposed a new kind of electricity distributor who can vary its energy need with tariff which led to much interest in developing aggregators' flexibility.

All these references solve a local optimization problem either at the consumer or at the market level rather than addressing the global problem of introducing flexibility at distributor level and analyzing its effect with respect to market and profits. Flexibility is the ability to respond i.e. to modulate its energy need with tariff. In our work, we propose a novel framework of a general grid taking into account flexibility.

More precisely, we propose a general interaction model which takes into account the developing diversity of actors in new electricity markets (Section 2). We describe the roles and specifics of each actor in the subsequent sections (producers, consumers, scheduling operators in Sections 3 to 5 respectively). We briefly comment on the demand market (Section 6). Finally, we present the simulator we have developed, written in Python (Section 7) and some preliminary results and observations obtained (Section 8).

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2 PROBLEM STATEMENT

Figure 1 represents the micro grid model which we study. Here, a scheduling operator, an aggregator, a reseller, and a windmill form a coalition and two such coalitions interact with each other through the demand market. We have simulated an hour ahead scenario of energy exchanges where both demand and production is flexible (i.e. adaptive to tariff) and compared it to the non flexible case. We formulated the situation as an optimizing problem, solving which gives optimal tariffs for the distributors and allows to assess the impact of flexibility in both energy savings and revenue maximization.

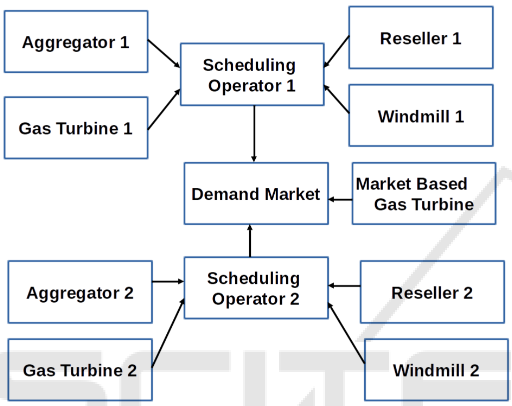

Figure 1: Interaction model among various actors of the micro grid.

3 MODELING OF THE PRODUCER

In this study, it is assumed that an *electricity producer* is either dealing with one and only one *scheduling operator* or directly selling energy on the demand market. Further, *producer* is a role corresponding to only one production means[1]. In this study, only windmills and gas turbines are taken into consideration.

3.1 Windmill

Since we are interested in an hourly interaction between the coalitions, one time investment costs are not considered. As thus the windmill is assumed to produce energy at cost 0. The windmills are always in contract with a scheduling operator and thus cannot contribute in the market. The production level of a windmill is partially uncertain and thus modeled as a random process. E_{wm} is the hourly energy production expectancy calculated on the basis of past history.

[1]There exist many production means: windmill, photovoltaic plant, hydro-power plant (over water, or in mountains), gas turbine, nuclear plants to name a few.

3.2 Gas Turbine

A gas turbine sells energy as requested by the scheduling operators or market. Thus, it charges the price as per amount of energy produced. Since we worked with real life data, we used the General Electric 9E gas turbine series and work of (Roche, 2012) to model the gas turbine pricing function as given by Equation (1).

Local Gas Turbine are in contract with a scheduling operator. Therefore, the scheduling operator buys from its contracted gas turbine before going to the market to buy extra energy if needed. $P^{\ell}_{gt}(E^{\ell}_{gt})$ denotes the cost for producing E^{ℓ}_{gt} amount of energy. E^{ℓ}_{max} is the maximum amount of energy that can be produced by the local gas turbine.

Market based Gas Turbine are similar to local gas turbines except they have no capacity constraint and are connected to the demand market. They have a higher charge than their local counterparts since they are not guaranteed to make profit via selling at every hour. $P^{m}_{gt}(E^{m}_{gt})$ is the price for selling E^{m}_{gt} amount of energy. While selling, the market based gas turbine keeps an additional constant profit margin $C^m > 0$ per unit of energy sold.

$$P^{\alpha}_{gt}(E^{\alpha}_{gt}) = 0.2(E^{\alpha}_{gt})^2 + (143 + C^{\alpha})E^{\alpha}_{gt} + 6088, \quad \text{with } \alpha \in \{\ell, m\}, C^{\ell} = 0, E^{\alpha}_{gt} > 0 \tag{1}$$

4 MODELING OF THE CONSUMER

We model the consumers and classify them into two broad groups. Those who are willing to accept a power offering which is less than the power they demanded, in exchange for a monetary compensation can be thought to draw power from a flexible distributor. Those with non flexible demand needs like hospitals can be labeled as a separate group who draw power from a non flexible distributor.

4.1 Reseller

The reseller is an actor in the smart grid, who serves as a non flexible distributor. It buys energy from the contracted scheduling operator and sells to its customers. It has no bound on the energy level it can sell.

For a reseller, T_r is the price per unit of energy at which it buys from the scheduling operator and E_r is corresponding amount of energy bought. C_r is the effective cost to the reseller and is given by $C_r = E_r T_r$.

4.2 Aggregator

An *aggregator* is in business with a *scheduling operator* and behaves as a flexible distributor. It has its own customers with their energy needs. The distinguishing role of an aggregator (compared to a reseller) is that it can influence its customers to reduce their energy needs with price incentives.

4.2.1 Flexibility Curve for Aggregator

Let us define the allotted energy ratio for the aggregator as

$$E_a^* = \frac{E_a}{E_{da}},$$

where E_a and E_{da} represent the energy allotted to the aggregator and actual demand of the aggregator respectively. The minimum allotted energy ratio that has to be provided is

$$E_{min,a}^* = \frac{E_{min,a}}{E_{da}},$$

where $E_{min,a}$ is the minimum energy that has to be consumed by aggregator even at infinite cost. E_a^* may be time varying while $E_{min,a}^*$ is kept constant and is fixed at 0.7. $E_{min,a}^*$ can be also made time varying so as to decrease it during hours of high requirement and increase in the opposite case.

Let T_a be the tariff charged to the aggregator. The tariff of the aggregator can be modeled by:

$$T^* = \frac{T_a}{T_r}.$$

The relation between E_a^* and T^* is given by a linear flexibility function

$$\phi(T_a) = 1 - \frac{T_a}{T_r} = 1 - T^*.$$

The proposed linear function for energy bought by aggregator is

$$E_a^* = \phi(T_a) + (1 - \phi(T_a))E_{min,a}^*, \text{ with } T_a \in [0, T_r]. \quad (2)$$

Equation (2) expresses the fact as T^* decreases, the energy satisfaction increases while at a higher tariff lower energy is consumed by the aggregator. Thus a flexibility is observed with respect to tariff charged to the aggregator.

Simplifying the algebra, the energy bought by aggregator E_a can finally be written

$$E_a = E_{da}\Big(1 - (1 - E_{min,a}^*)T^*\Big), \quad \text{with } T^* \in [0,1].$$

The effective price charged by the scheduling operator can then be calculated by multiplying the amount of energy sold by per per unit price:

$$C_a(E_a^*) = T_a E_a = E_{da} E_a^* T_r \frac{1 - E_a^*}{1 - E_{min,a}^*}. \quad (3)$$

4.2.2 Compensation Function

Although selected through trial and error, the rationale behind a compensation function is that the compensation tariff should be more than the buying tariff. Consequently, the larger the unsatisfied energy, the larger the penalty incurred. The sample function which is used for this model is given by

$$F_c(E_a^*) = (1 - E_a^*)E_{da}^* T_r \log(T_r). \quad (4)$$

5 DEFINING THE SCHEDULING OPERATOR

A *scheduling operator* is an actor connected with several electricity producers and one or several electricity distributors. Its responsibility is to equilibrate production with consumption. If the suppliers, with whom it is dealing with, cannot provide enough energy, it can buy electricity on the demand market. Reciprocally, if the consumption is lower than the production, it can sell excess energy on the market.

5.1 Market Strategy

Each scheduling operator needs to develop an expectation of market demand per hour. In addition to that, it needs to formulate its buying and selling valuation functions for E_x, the energy in exchange with the market. The convention is $E_x > 0$ if the scheduling operator buys from the market and $E_x < 0$ if the scheduling operator sells to the market. Underlying the energy exchange, lies the energy conservation law, which can be formulated in our case by

$$E_{wm} + E_{gt}^{\ell} + E_x = E_r + E_a. \quad (5)$$

Selling to the Market. The selling price for $|E_x|$ amount of energy comes from the difference of production cost for total amount of energy generated by the local gas turbine given by E_{gt} and the production cost for the supply of energy supplied to the aggregator and reseller which is $E_{gt} + E_x - E_{wm}$. The selling price is of the same sign as E_x, and therefore non positive by convention and its absolute value is the excess cost for producing $|E_x|$:

$$P_{s,m}(E_x) = P_{l,gt}(E_{gt}^{\ell}) - P_{gt}^{\ell}(E_{gt}^{\ell} - E_x). \quad (6)$$

Buying from the Market. An amount E_x of energy can be bought either (i) from a selling scheduling operator or (ii) from the market gas turbine or (iii) a contribution from both. So the buying price estimation of a scheduling operator is taken in between the expected selling price of that amount by the other scheduling operator and by the market-based gas turbine:

$$P_{b,m}(E_x) = (\gamma - 1)P_{s,m}(E_x) + \gamma P_{m,gt}(E_x). \quad (7)$$

where γ is a parameter between 0 and 1. A high value of γ signifies that the energy is more likely to come from the market gas turbine, while a lower value denotes likeliness to come from the selling scheduling operator. Since the pricing function of the other scheduling operator for $|E_x|$ amount of energy is unknown, we assume each scheduling operator expects the other to value $|E_x|$, the same way it would have. Thus the expected market function is given by

$$P_m(E_x) = \begin{cases} P_{s,m}(E_x) & \text{if } E_x < 0, \\ P_{b,m}(E_x) & \text{otherwise.} \end{cases} \quad (8)$$

Finally, the value of γ is learned through past experiences.

5.2 Utility / Profit for the Scheduling Operator

Utility U represents the profit made by any scheduling operator. It is formulated as the revenue obtained in selling to the aggregator and the reseller minus the production cost from the local gas turbine, buying cost from the market, and the compensation to the aggregator:

$$\begin{aligned} U(E_a^*, E_x, E_{gt}^\ell) = C_r + C_a(E_a^*) - P_m(E_x) \\ -P_{l,gt}(E_{gt}^\ell) - F_c(E_a^*). \end{aligned} \quad (9)$$

Note that with the previous conventions $P_m(E_x)$ is non negative if the scheduling operator is buying energy from the market and non positive otherwise. The strategy of the scheduling operator (SO) is then:

$$\max_{E_a^*, E_x, E_{gt}^\ell} U \text{ s.t. } \begin{cases} E_{wm} + E_{gt}^\ell + E_x = E_r + E_a^* E_{da}, \\ E_a^* \in [E_{min,a}^*, 1], \\ E_{gt}^\ell \in [0, E_{max}^\ell]. \end{cases} \quad (10)$$

The demand market (presented below) has the property to always allocate the demanded amount to the buying SO (i.e. those with $E_x > 0$) while satisfying partly or totally the selling SO: that is the amount to be sold is $|\widetilde{E_x}| \leq |E_x|$ if $E_x < 0$. Hence, for both SO, the optimization (10) is solved *before* entering the market. Then, for the selling SO, optimization (10) is solved again *after* the allocation of the market, with the extra constraint that for that SO with $E_x = \widetilde{E_x}$.

6 MODELING THE DEMAND MARKET

At the start of each hour, the two scheduling operators report to the market their willingness to either sell or buy energy. Three cases can arise:

Buying and Selling Scheduling Operator. Scheduling operator 1 wants to buy $E_x^1 > 0$ amount of energy while scheduling operator 2 wants to sell $E_x^2 < 0$. Thus scheduling operator 2 submits a two dimensional selling bid of the form $\langle E_x^2, P_x^2 \rangle$. The market computes prices P_A and P_B according to:

$$\begin{cases} P_A = P_x^2 \times \min\left(\frac{E_x^1}{|E_x^2|}, 1\right) + P_{gt}^m\left(\max\left(0, E_x^1 - |E_x^2|\right)\right), \\ P_B = P_{gt}^m(E_x^1). \end{cases}$$

The buyer gets the amount E_x^1 of energy (as expected) and is charged $P_x^1 = \min\{P_A, P_B\}$. If $P_B < P_A$, then the seller gets $\widetilde{P_2^x} = 0$ and the market gas turbine receives P_B. Otherwise, the selling scheduling operator sells the amount of energy $\widetilde{E_x^2} = \min\left(\frac{E_x^1}{|E_x^2|}, 1\right) \times E_x^2$ at total price $\widetilde{P_x^2} = \min(\frac{E_x^1}{|E_x^2|}, 1) \times P_x^2$.

Buying Scheduling Operators Only. Let the buying scheduling operators report their demand E_x^1 and E_x^2. The market fetches the total demand of $E_x^1 + E_x^2$ from the market based gas turbine at a price of $P_{m,gt}(E_x^1 + E_x^2)$ and the buyers are charged a payment proportional to the energy they requested for.

Selling Scheduling Operators Only. When both scheduling operators try to sell, then no energy transaction takes place in the market. Thus both the scheduling operators receive a payment of 0.

7 IMPLEMENTATION

Each scheduling operator plans each hour ahead and thus saves itself from producing any unused amount of energy. At each hour of simulation, the scheduling operator gets information on expected amount of production from the windmill. Information is fed into the Equation (9) to give out the answers of how much local gas turbine should produce and also how much to buy or sell to the market.

Then, the reseller and aggregator attached with a scheduling operator reports its demand for that hour. As for the simulation, web service is used to relay the information to the scheduling operator. Once the

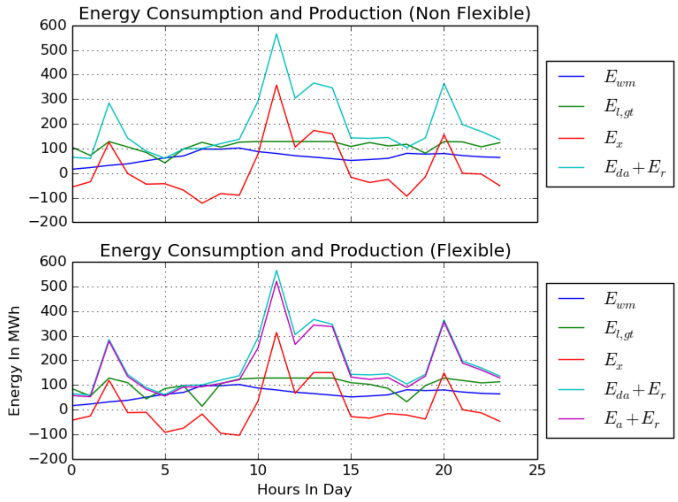

Figure 2: Energy Production and Consumption Comparison.

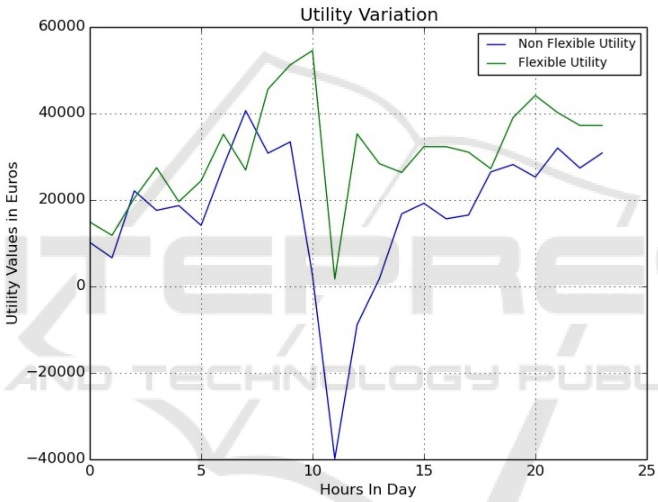

Figure 3: Utility Value Comparison.

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market plays its role, the scheduling operators adjusts their production and consumption.

The simulation was implemented in Python 3.4 using Flask API on commodity hardware. Each actor was assigned a server port address and communication between different actors was carried via HTTP protocol. The results were later converted into graphs for visualization using matplotlib.

8 RESULTS AND DISCUSSION

Results can be divided into two parts, the first task being to find tariff T_r of each coalition. The second task is to understand the impact of flexibility on the smart grid model in terms of profit made.

8.1 Finding Tariff

In order for the optimization to work, we have to set the tariff for distributors such as aggregators and resellers. Initially, random prices were chosen to see how the system behaved. It was observed that on setting the tariff too high, the aggregators started behaving like resellers. On lowering the tariff, the scheduling operator on behalf of its coalition made immense losses. Then, we tried to find the best tariff for each hour for which there were no losses nor profit for the scheduling operator, assuming aggregators to be resellers as well. The average tariff was then calculated over a year. For Scheduling Operator 1 and Scheduling Operator 2, as given in the model, the tariff came as 300€/MWh and 320€/MWh respectively. To make the model simple, we have assumed that the tariffs are time invariant.

8.2 Impact of Flexibility

To understand the impact of flexibility, a similar situation with non flexible operator in one case and flexible operators on the other must be compared. Here study has been mainly focused with respect to two parameters namely energy consumption and production and utility variation. A randomly sampled result has been put to display.

The plots in Figure 2 show the need of flexibility in the hours of high demand. It is justified since it is not wise to trouble the customers all the time as that might lead to undesirable circumstances. For example, in the 11^{th} hour, there was an imminent need for flexibility after the local gas turbine reached its maximum operating point. The plots in Figure 3 show the variation of utility/profit in both cases. It can be observed that at the time of flexibility, the non flexible operator incurred a loss while the flexible one made a profit, no matter how meager it is. From an economical standpoint, flexibility resulted in a better utility than being non flexible keeping the other parameters constant.

9 CONCLUSION

In this paper, though we have kept the mathematical modeling simple, the impact of flexibility at aggregator level have been quite prominent. The naive way of finding an optimal tariff, seemed effective in showing flexibility. More importantly, the system showed flexibility only in times of high demand, automatically modeling the comfort level of the consumers. Finding out the optimal tariff for the system is worth researching as it is one of the critical parameter for the system to show flexibility. Instead of keeping it constant throughout the day, it can made to vary along different hours of the day. There is lack of strategies in the paper, by virtue of which a scheduling operator can model others. Possible scopes of experimenting lies in formulation of the flexibility function and compensation function for the aggregator. The interaction between the scheduling operators via the market can be thought of as an auction mechanism. Herein lies the future scope of game theory into modeling the expectation function for the scheduling operators along with bidding strategies. With more than two scheduling operators in the market, the grid dynamics will be interesting to observe.

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