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Impact of Load Shifting on the Profit of Electricity Retailer based on Demand Response and Risk Management

Kourosh Apornak[1], Soodabeh Soleymani[1]*, Faramarz Faghihi[1], Babak Mozafari[1]

[1] Mechanic, Electric and Computer Department, Science and Research Branch, Islamic Azad University, Tehran, Iran.

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Abstract

This paper aims to describe the role of electricity retailer in power market for persuading consumer to shift their loads. It presents the influence of load shifting on retailer profit and risk management in market environment. In this problem, retailer participates in bilateral contract, also stochastic programming is used to manage the uncertainties of pool prices and elasticity of consumer. It shows that by participating retailer in market contract, the retailer profit will be changed. This paper also analyzes the consumer behavior when the load is shifted from the time with high price to the time with low price. The tariff of demand response program used in this paper is Time of use pricing for the periods of week. Risk Measuring is done by Value at Risk (VaR) and Conditional Value at Risk (CVaR) in this study.

Keywords: Demand response program, Load shifting, Power market, Retailer, Risk management.

1. INTRODUCTION

Electric deregulation is the route of changing laws that controls the electric industry to provide customers with the choice of electricity suppliers who are either retailers or agents by allowing competition. Deregulation can develop the economic effectiveness of the production and use of electricity. Because of electric industry competition, the power price is expected to decrease and so the consumers profit.

Reference [1] Estimated thermostat set point control of aggregate electric water heaters (EWHs) for load shifting, and prepared required balancing reserve for the utility. It also considered the economic profits

***Corresponding Author's Email:**
soodabeh_soleymani@yahoo.com

of Demand Response for the consumers within time-of-use pricing.

Internet of Energy framework to examine the peak load shifting problem was studied in [2]. Where customers in the energy market could adopt their respective energy storage facilities to charge and discharge energy with the purpose of minimizing the total operating costs. In such a problem setting, every customers can be demander and supplier in the energy market, so that operating costs are involved; the energies from both traditional electrical systems and distributed renewable energy sources can be stored in energy storage facilities; real-time price of energy will be used adequately to influence energy distribution of supply and demand.

Unique definition can be used for peak load shifting that shifts the energy usage demand during the peak load time to the off-peak load time with low energy demand. For example, in 1990s [3], the energy load management to reduce energy consumption and to organize proper power-generating schedules to reach the aim of peak load shifting was applied. Note that adjusting load is a common strategy to develop the performance in other fields, like load reduction multimedia data [4].

The work in [5] investigated the electricity demand of grids using a mathematical model for the home energy management system in order to save the energy consumption of home appliances as well as various energy storage facilities and to prevent any peak load of systems.

A sudden load billing scheme was adopted [6] in order to shift consumers peak hour demand and to charge them equally for their energy consumption. In [7], utility companies and residential users were formed in two levels, which reduce demand variation and peak load.

Theoretical and quantitative analysis of the useful influence of demand shifting (DS) in lessening market power by the generation side was presented in [8] for the first time. Quantitative analysis was proposed by a multi-period equilibrium programming model of the imperfect electricity market, accounting for the time-coupling operational constraints of DS as well as network constraints.

One of the main approach in [9] was demand response, as a key section of smart grid technology. Demand response may keep the balance of power supply and demand by peak load shaving. In demand response programs, real-time pricing (RTP) is viewed as a useful method to handle price-responsive loads. According to [9], in load shifting context, load reduction is more common, load reduction during certain times is done by a load recovery effect during preceding or succeeding periods. This shift of energy demand from high- to low-price periods causes a demand profile flattening effect.

Though several studies have explored the impacts of demand shifting (DS) on various looks of power system operation and planning [10]-[15], its impact in imperfect electricity markets has not been broadly explored yet. DS flexibility in an imperfect electricity market model through also considering the cross-price elasticity of the demand side was developed in [16], but no theoretical or measureable analysis of the specific impacts of demand shifting on strategic producers market power was offered.

Methods for employing customers into DR efforts include price-based DR programs via time-varying price mechanisms such as time-of-use (TOU) pricing, critical peak pricing, variable peak pricing, and real-time pricing, as well as incentive-based direct load control DR programs for providing power utilities and

ISOs abilities to cut down/shift loads from peak periods to off-peaks [17]. Although, the price-based DR is not still used broadly, a comparison of TOU and real-time pricing [18] shows that real-time pricing signals will carry on more real-time operation information of power systems, which would cause more benefits to power systems in terms of flattening system load profiles and reducing peak demands as compared to TOU rates. This paper emphasizes price-based demand response programs with real-time pricing.

Demand response management needs to be properly planned in order to reliably measure the benefits of demand response options and guarantee that both suppliers and customers are cost-effective and effective at providing needed demand reductions [19]. Also, the price-based DR needs to be improved so that customers are able to take control of their electricity costs with instable real-time pricing [20]. Additionally, although a high penetration of price-sensitive demand response loads would help to decrease the peak electricity prices, MCPs over time may still not be perfectly flat due to capacity limitations and minimum on/off time constraints of generating units, even if all loads fully participate into the price-based demand response program [21]. Price-sensitive demand response causes additional dynamics and new challenges to the real-time supply and demand balance. Specially, if real-time price based demand response programs are widely deployed in future, price-sensitive demand response load levels would constantly change in response to dynamic real-time prices, and the changes in DR loads will impact the economic dispatch plan and in turn affects the electricity market clearing prices.

Closed-loop method design was analyzed [22] to power markets using eigenvalues. In [23], authors supposed that both power suppliers and consumers respond to real-time market prices are uninterruptedly increasing or reducing their sales or purchases, and it explores how the market results could deviate from the competitive situation.

Case studies demonstrate that the time-shifting flexibility of the consumers decrease the retailer revenue, since consumers can respond more effectively to strategic retail pricing samples, but also decrease the retailer cost, as it leads to flatter wholesale demand and price profiles, an effect which is not captured by former work [24]. The retailer can profit from the flexibility in demand side in some cases. The flexibility also leads to lower spot prices so that the customers in real-time price-based demand response enforce the lower electricity price for per-unit power consumption [25]. In half-term planning, the objective of an electricity retailer is to procure the electricity energy to supply its demands, while efficient control of the financial risks under uncertainties is as biotic as maximizing profit [26]. Optimal provision of electricity from wholesale market to minimize the provision cost and optimal selling price calculation considering a price responsive demand, to maximize income. On the provision side, retailer faces uncertainty of pool electricity price and at sell side, it sets selling price based on the elasticity of its consumer demand. The work contributes by highlighting the impact of demand behavior on a retailer decision making for different price elasticity and providing informed decision support under pool price uncertainty to address different risk-averse nature of retailers [27].

The main contributions of this paper are listed in following.

1) Propose a logic model for retailers trading in pool based electricity markets and through bilateral contracts to persuade

consumers for shifting their consumption in low pool prices.

2) Formulate the stochastic model as a nonlinear programming problem which can be effectively solved by using proper software.

3) Manage and study the risk that retailer must be tolerate by using CVaR and VaR view.

The used symbols and their definition to make the paper readable are listed in following.

α=Confidence level

b=Index for time periods for trading in bilateral market

m=Index for months

j=Index for customers

r=Index for time periods for trading in pool market

t=Index of time for trading with customers

ω=Index of scenarios

F_0=Expected profit of the retailer before shifting load

F_L=Expected profit of the retailer after shifting load

R_ω=Profit of the retailer for scenario $\boldsymbol{\omega}$

ΔF=Change in the expected profit

$\Delta P^{C}_{jt\omega}$= rate of change of the power for the customer j, period t and scenario $\boldsymbol{\omega}$

$\Delta\lambda^{C}_{jt}$= rate of change of the price for the customer j, period t

$E_{jt\omega}$= Elasticity of the customer j, period t and scenario $\boldsymbol{\omega}$

L^{B}_{b} =Number of hours of period b

L^{C}_{t} = Number of hours of period C

N_B= Number of time periods considered to trade through bilateral contracts

N_J= Number of all customers

N_T= Number of time periods considered to trade with customers

N_R= Number of time periods considered to trade through pool

N_ω= Number of scenarios

P^{B}_{b}= power bought through bilateral in period b

P^{c}_{jt}= the power contracted in period t for customer j

λ^{c}_{jt}= Price of the energy for customer j in period t

λ^{B}_{b}= Price of the bilateral contracts in time period b

$\lambda^{P}_{r\omega}$= Price of the pool in time period r and scenario $\boldsymbol{\omega}$

ξ = Auxiliary variable used to calculate the CVaR ($).

η_ω = Auxiliary variable related to scenario ω used to calculate the CVaR ($).

A = Confidence level used in the calculation of the CVaR.

π_ω= Probability of occurrence of scenario ω.

θ_{tr}= Relationship between time period r and t

Ω_{rb}= Relationship between time period b and r

Λ_{tm} = Relationship between time period m and t.

2. RELATIONSHIP BETWEEN RETAILER, DEMAND RESPONSE AND CONSUMPTION MANAGEMENT

For any retailer, there are two types of contracts, buying energy and selling energy, usually part of buying and selling energy through instantaneous energy, where there are a lot of price fluctuations. On the other hand, the retailer is committed to provide the variable energy for consumers.

While the retailer faces load fluctuations and price, consumers who face fixed price of electricity show less sensitivity towards the price changes in the wholesale market. Increasing the consumer sensitivity is followed by advantages like decreasing the production cost, decreasing authority in the market, and decreasing the costs paid by the consumers. Applying methods which increase the consumers sensitivity could be advantageous both for the total system and the consumer as well. In order to solve this problem and increase the consumers sensitivity, the pricing models which vary with time like real time pricing, time use pricing, and critical-peak pricing were proposed.

The main objective of these pricings is summarized as,

1. Retailer price which reflects the wholesale market fluctuations to the final consumers so that they pay based on the real value of electricity in different times of the day.
2. Encouraging the consumers to change working hours of the high consumption devices to non-peak hours to decrease their own costs and help to decrease the peak to medium load ratio

By regarding all things described above, real time pricing (RTP) of electricity provides natural transmission of price signals from real-time market to small consumers. While real time pricing, consumers face hour prices which change daily and they decide based on these prices. In addition, real time pricing eliminates the risk of buying electricity which the retailer or the local distribution company might face due to buying from the wholesale market or the unstable instantaneous prices and selling it with fixed price. Also, employing instantaneous pricing transfers the price risk from the retailer or the local distribution company to the final consumer.

2.1. Demand Response Program and TOU Pricing

Demand response occurs when an electricity consumer reduces their energy demand at specific times of power system need – either in response to change in electricity price or to incentives during peak period. During such times wholesale market prices for electricity may be high, the power system is experiencing large peaks in demand, or there is a high risk for the electricity grid reliability.

Demand response can be used into the energy cost-management strategy in different ways for electricity market. During peak periods, reduce the consumption by curtailing the facilities electricity usage or switching to on-site generation. Shifting production to an off-peak period is another opportunity to take advantage of lower electricity costs.

In this paper, TOU tariffs are used. In this type of tariff, although the rate is rigid for the duration of the contract, it depends on the time of day. Time-of-use rate plans better align the price of energy with the cost of energy at the time it is produced. Lower rates during partial-peak and off-peak hours offer an incentive for customers to shift energy usage, away from more expensive peak hours, which can help the customers save money and reduce strain on the electric grid.

2.2. Risk Measurement

The measuring of the risk modeled in this study is done by VaR and CVaR. Value at risk is a measure of the risk of loss for investments. It estimates how much a set of investments might lose (with a given probability and normal market conditions) in a set time period such as a day. VaR is typically used by firms and regulators in the financial industry to gauge the amount of assets needed to cover possible losses. For a given portfolio, time horizon, and probability p, the p VaR can be defined informally as the maximum possible loss during the time if we exclude worse outcomes whose probability is less than p.

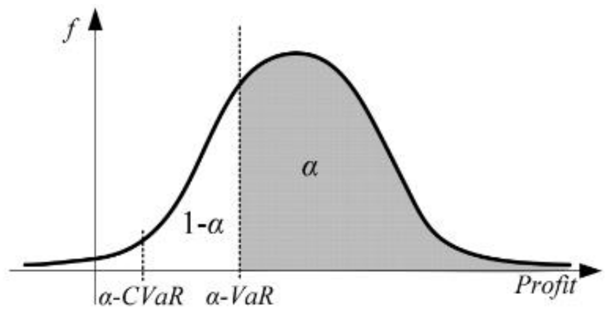

Fig. 1. Concept of VaR and CVaR for risk measurment.

This assumes mark-to-market pricing, and no trading in the portfolio[28].

Conditional value at risk is a risk assessment technique often used to reduce the probability that a portfolio will incur large losses. This is performed by assessing the likelihood (at a specific confidence level) that a specific loss will exceed the value at risk. Based on mathematic, CVaR is derived from a weighted average between the value at risk and losses exceeding the value at risk.

The CVaR at the α confidence level can be expressed as the expected profit of those scenarios related to the lower tail of the profit distribution, for example, scenarios whose profits are lower than or equal to (1-α) quantile of the profit distribution (see Fig. 1). Note that VaR is defined as (1-α) quantile of the profit distribution.

$$CVar = Maximize_{\xi,new}$$

$$\xi - \frac{1}{1-\alpha}\sum_{\omega=1}^{N}\pi_\omega\eta_\omega \tag{1}$$

$$\xi - \sum_{t=1}^{N_T}\left(\sum_{e=1}^{N_E} R_{etw}^{R} - C_{tw}^{P} - C_t^{F}\right) \le \eta_\omega, \forall\omega$$
$$\eta_\omega \ge 0, \ \forall\omega \tag{2}$$

The ideal rate of ξ is a risk measure accepted as Value-at-Risk (VaR), is the profit of scenario, and η_ω is an auxiliary positive variable which is equal to the difference of VaR and the profit of scenario ω

3. STOCHASTIC PROGRAMMING

Stochastic programming is a framework for modeling optimization problems that involve uncertainty. In this problem, the retailer meets two sources of uncertainty: pool prices and price elasticities of the customers. Pool prices rely on the bids suggested by the market operator, and assuming a price-taker retailer, they are independent of the retailer actions. Price elasticities of the customers are also uncertain and free of the retailer choices, finally uncertainty in pool prices and customer elasticity explain via scenarios. Each scenario has a probability of happening π_ω , in such a way that the sum of the probabilities over all scenarios is equal to 1.

3.1. Problem Formulation

In general, the retailer profit in the electricity market can be shown as follows:

Difference between the revenue obtained from selling energy to consumers and the cost of involvement in pool agreements and buying energy from bilateral agreements, so the final profits depends on stochastic prices of pool and customers demands [8]. For obtaining the retailer profit before load shifting, Eq. (3) is used:

$$F_0 = \sum_{t=1}^{N_T}\sum_{j=1}^{N_J}\lambda_{jt}^{c}P_{jt}^{c}L_t^{C} - \sum_{b=1}^{N_B}\lambda_b^{B}P_b^{B}L_b^{B}$$
$$-\sum_{\omega=1}^{N_W}\sum_{t=1}^{N_T}\sum_{r\in\theta_{tr}}\pi_\omega\lambda_{r\omega}^{P}L_r^{P}\left(\sum_{j=1}^{N_J}P_{jt}^{C} - \sum_{b\in\Omega_{rb}}P_b^{B}\right) \tag{3}$$

Also, the retailer profit after load shifting can be shown by Eq. (4) to inspire customers to shift their load from periods related with high pool prices to periods with low pool prices, the retailer modifies selling prices λ_{jt}^{C}:

$$F_L = \sum_{\omega=1}^{N_W} \sum_{t=1}^{N_T} \sum_{j=1}^{N_J} \pi_\omega (\lambda_{jt}^C + \Delta\lambda_{jt}^C) \times (P_{jt}^C + \Delta P_{jt\omega}^C) \;\; L_t^C - \sum_{b=1}^{N_B} \lambda_b^B P_b^B L_b^B + \sum_{\omega=1}^{N_W} \sum_{r=1}^{N_R} \pi_\omega \lambda_{r\omega}^P L_r^P \sum_{b\in\Omega_{rb}} P_b^B - \sum_{\omega=1}^{N_W} \sum_{t=1}^{N_T} \sum_{r\in\theta_{tr}} \pi_\omega \lambda_{r\omega}^P L_r^P \sum_{j=1}^{N_j} (P_{jt}^C + \Delta P_{jt\omega}^C) \quad (4)$$

By defining Eq. (4), now describing the expected profit of retailer is easy:

Expected profit achieved by a retailer is calculated as incomes from selling energy to consumers, minus costs from buying energy within a bilateral contract and minus costs from buying energy in the pool contract.

The price elasticity of consumer is described as,

$$E_{jt\omega} = \frac{-\Delta P_{jtw}^C / P_{jt}^C}{\Delta\lambda_{jt}^C / \lambda_{jt}^C} \quad (5)$$

The retailer tracks to maximize the modification in the expected profit, the objective function for retailer could be illustrate as,

$$\Delta F = \sum_{\omega=1}^{N_W} \sum_{t=1}^{N_T} \sum_{j=1}^{N_J} \pi_\omega (1 - E_{jt\omega})\, \Delta\lambda_{jt}^c P_{jt}^c L_t^C - \sum_{\omega=1}^{N_W} \sum_{t=1}^{N_T} \sum_{j=1}^{N_J} \pi_\omega \frac{E_{jt\omega} P_{jt}^c L_t^C}{\lambda_{jt}^c} (\Delta\lambda_{jt}^c)^2 + \sum_{\omega=1}^{N_W} \sum_{t=1}^{N_T} \sum_{r\in\Theta_{tr}} \sum_{j=1}^{N_J} \pi_\omega \frac{E_{jt\omega} P_{jt}^C}{\lambda_{jt}^c} L_r^P \lambda_{r\omega}^P \Delta\lambda_{jt}^c \quad (6)$$

Objective function in Eq. (6) would be the optimization according to Eqs. (7-12):

$$\underset{\Delta\lambda_{jt}^C\, \forall j,t,\xi,u_\omega\ \forall\omega}{Maximize} \quad \xi - \frac{1}{1-\alpha} \sum_{\omega=1}^{N_W} \pi_\omega u_\omega \quad (7)$$

$$-\sum_{\in \Lambda_{tm}} \frac{E_{jt\omega} P_{jt}^c L_t^C}{\lambda_{jt}^c} \Delta\lambda_{jt}^c = 0; \quad \forall j, \forall m, \forall\omega \quad (8)$$

$$\sum_{t=1}^{N_T} (P_{jt}^C - \frac{E_{jt\omega} P_{jt}^C}{\lambda_{jt}^c} \Delta\lambda_{jt}^c) L_t^C (\lambda_{jt}^C + \Delta\lambda_{jt}^c) - \sum_{t=1}^{N_T} \lambda_{jt}^c P_{jt}^c L_t^C \le 0; \qquad \forall j, \forall\omega \quad (9)$$

$$-aP_{jt}^C \le -\frac{E_{jt\omega} P_{jt}^C}{\lambda_{jt}^c} \Delta\lambda_{jt}^c \le aP_{jt}^C \quad \forall j, \forall t \in \Lambda_{tm}, \forall m, \forall\boldsymbol{\omega} \quad (10)$$

$$\lambda_{jt}^C + \Delta\lambda_{jt}^c \ge 0; \qquad \forall j, \forall t \quad (11)$$

$$P_{jt}^C - \frac{E_{jt\omega} P_{jt}^C}{\lambda_{jt}^c} \Delta\lambda_{jt}^c \ge 0 \qquad \forall j, \forall t, \forall\omega \quad (12)$$

The objective function (7) which should be maximized, contains the CVaR of the profit at the confidence level α.

Constraints (8) insist that the energy consumed by each customer during a month cannot be changed, it means that welfare of the customer cannot be decreased because of high electricity prices and only load shifting between the time periods of each month is permited.

Constraints (9) insist that the expense of no customer can increase. The first term shows the payment of a customer after price changes though the second term shows the primary payment of the customer.

Constraints (10) enforce demand ramp rate bounds for per month.

Constraints (11) express that the selling prices after modifications must be positive.

Constraints (12) assure that the power used up by each customer after load shifting is positive.

3.2. Problem Data

We count a retailer working in a power market and a time limit of 1 month for bilateral contract. Hourly pool prices are collected in 6 periods, and agreements signed between the retailer and the consumers are time-of-use pricing, where two periods are studied for each month. The choice of 6 values for every month is driven by the pool price performance in the Iberian electricity market [25] to show the sequential deviation of the electricity pool price during a month.

The retailer sells energy to a group of 100 customers separated into three groups with related features about a) selling prices, b) consumption configurations, and c) reaction to the price suggested by the retailer (elasticity). The three kinds of customers are residential (84 customers), commercial (12 customers) and industrial (4 customers). Power consumption for peak and off-peak periods is about 3.6 kW and 2.9 kW for residential customers, about 60 kW and 49 kW for commercial customers, and about 3.3 MW and 2 MW for industrial customers. Selling price for peak and off-peak periods is about 94 €/MWh and 88 €/MWh for residential customers, around 88 €/MWh and 82 €/MWh for commercial customers, and about 80 €/MWh and 73 €/MWh for industrial customers. The retailer has contracted a bilateral contract of 7 MW at 75 €/MWh for the counted time horizon. This quantity relates to almost the 60 of the total power sold to customers.

Totally 800 scenarios have been selected, 40 pool prices scenarios are made for one month peryear. Moreover, 20 elasticity scenarios are counted in the model which have been made accidentally using a normal distribution with mean and standard deviation values 1.25 and 0.03 for residential customers, pairs (1.1, 0.05) and (1.4, 0.08) for commercial and industrial customers in order.

Constant α is 0.20, which indicates a maximum power variation of 20 is permitted.

3.3. Problem Timing

It is assumed that a retailer participates in a pool-based power market (buying or selling energy), buying energy throughout bilateral contracts and selling energy to customers throughout contracts.

The time framework for pool exchange in this study is six time blocks representing the level of pool prices. The time blocks are named Saturday peak, Saturday off-peak, working day (Sunday-Thursday) peak, working day off-peak, Friday peak, and Friday off-peak. Peak period varies from 12 A.M. to 11 P.M. whereas off-peak period ranges from 12 P.M. to 11 A.M.

4. SIMULATION RESULTS

Stochastic problem (7)–(12) is answered to determine the price variations to persuade customers to shift their consumption. The subject is a nonlinear programming problem which is solved using MINOS within Package GAMS on a Windows-based server with one processor clocking at 2.30 GHz and 6 GB of RAM. Confidence level is considered to be equal to 0.9.

Fig. 2 depicts price variations for residential customers throughout peak periods. In this period, for encouraging customers to reduce their consumption when pool prices are high, the retailer will increase the selling price.

Fig 3 shows price variation for residential customers throughout off-peak periods, for this period, retailer will decrease the selling price for the off-peak period to achieve the opposed performance of the customers. Obviously, the price variations are higher for customers who have lower elasticity rates. Some of this 84 customers are not agree to vary their consumption, so, the prices related with their tariffs do not change.

Fig 4 illustrates the mean rates for variations in the power consumed by residential customers for peak periods and Fig. 5 shows the power variation for off-peak periods, As usual, the general movement is that customers decrease their consumption in the peak period whereas increase it in the off-peak period, causing in a flatter load duration curve.

It is known that many customers are not eager to change their consumption, it should be noted that the energy consumed by each customer during the time horizon must be fixed.

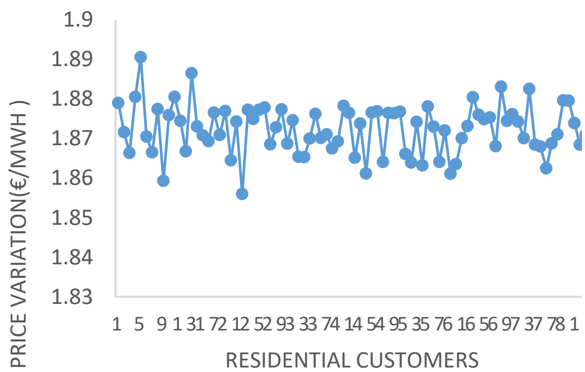

Fig. 2. Price variation of residential customer in peak periods.

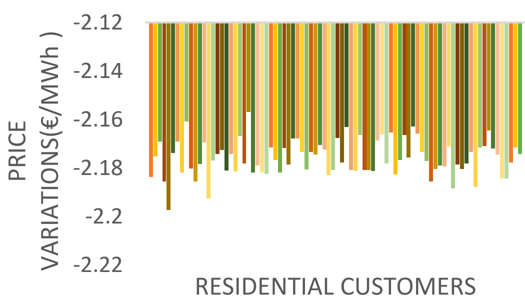

Fig.3. Price variation of residential customer in off-peak periods.

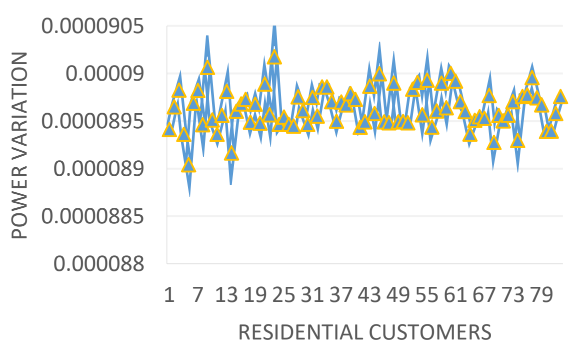

Fig. 4. Power variation of residential customer in peak periods.

Fig. 6 shows some selected scenarios and profit for the retailer related to that scenarios. By this scenarios, the retailer makes a better performance in power market, and the retailer is able to make the best decision in dealing with its customer.

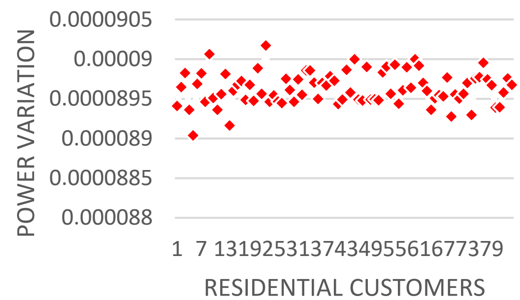

Fig. 5. Power variation of residential customer in off-peak periods.

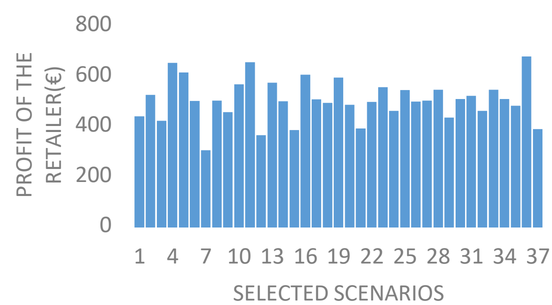

Fig. 6. Profit of the retailer for selected scenarios.

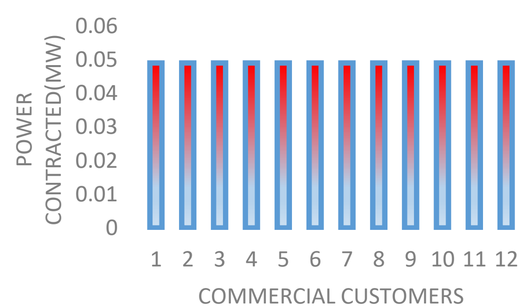

Fig. 7. Power contracted by the commercial customers.

Fig. 7 shows the power contracted between commercial customers and retailer. This value completely affect the retailer profit both after and before load shifting, i.e. (F_0) and (F_L). Figs. 8 and 9 are corresponded to Eqs. (1-2-7), which illustrate the risk simulation and risk management.

Fig. 8. Expected profit versus confidence level (α=in risk measuring).

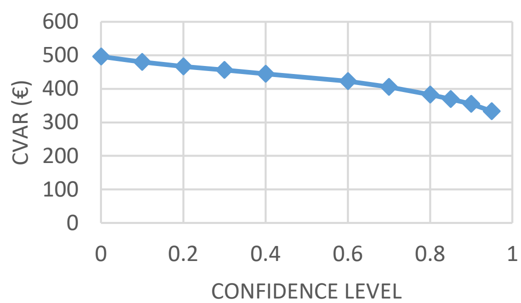

Fig. 9. Relationship between confidence level and CVaR.

Fig. 8 shows the relation between expected profit vs confidence level (α), when confidence level increases, lower changes in energy prices are forced by the retailer, and then, the load redistribution decreases.

Fig. 9 displays the relationship between CVaR and confidence level, when the confidence level raises, the retailer is eager to adopt the low risk and achieve key results.

The reflecting problem shows the more risk opposed case, where the retailer is only to maximize the lowest rates of the profit distribution, it causes the lowest expected profit.

5. CONCLUSION

This paper proposed a model, according to stochastic programming, which lets a retailer to fix the price changes in order to motivate customers to shift their loads between time periods. The retailer is interested in bending the customer consumption with its energy availability, reducing the energy purchased in the pool-based electricity market. The retailer looks uncertain pool prices and uncertain price elasticities for customers. The risk of the retailer profit is developed by using CVaR. For future research, it would be interesting to use game theory formulation between two or more retailer to define a sales prices for encouraging customers to participate on its own program. Furthermore, it would also be exciting to develope the model for defining alternative tariff, like interruptible tariffs.

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