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A MODEL FOR DEFINING THE RETAILER'S PROFIT BASED ON LOAD SHIFTING AND TOU PRICING

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ABSTRACT

Deregulation of the electricity market is an important issue in the energy sector. A major aim of deregulation is to increase competition among electricity retailers/suppliers and thereby enrich consumer choice among electricity products Retail energy markets are the final link in the energy supply chain. Energy retailers buy electricity in wholesale markets, package it with transportation services and sell it to customers. This is typically the main interface between the electricity industry, and customers such as households and small businesses. The electricity retailers are simply competing for the right to send a customer a bill, to package up a range of tariffs and lock the customers into a contract, also the opening to competition into retail electricity supply gives the opportunity to consumers to choose their own supplier. This paper analyze the profit of the retailer based on demand response(DR) and participation of customer in DR programs, also in this paper we consider stochastic programming and risk modeling of the retailer by LODA SHIFTING.

KEYWORDS: Electricity Retail market, TOU pricing, profit, Risk Modeling, Deregulation

INTRODUCTION

Electric deregulation is the process of changing rules and regulations that control the electric industry to provide customers the choice of electricity suppliers who are either retailers or traders by allowing competition. Deregulation improves the economic efficiency of the production and use of electricity. Due to competition in the electric industry, the power prices are likely to come down which benefits the consumers.

The main objectives of the deregulated power market:

• To provide electricity for all reasonable demands.
• To encourage the competition in the generation and supply of electricity.
• To improve the continuity of supply and the quality of services.
• To promote efficiency and economy of the power system.

One of the another main of this paper is the use of DEMAND RESPONSE (DR) in power system; Demand response provides an opportunity for consumers to play a significant role in the operation of the electric grid by reducing or shifting their electricity usage during peak periods in response to time-based rates or other forms of financial incentives. Demand response programs are being used by some electric system planners and operators as resource options for balancing supply and demand. Such programs can lower the cost of electricity in wholesale markets, and in turn, lead to lower retail rates. Methods of engaging customers in demand response efforts include offering time-based rates such as time-of-use pricing, critical peak pricing, variable peak pricing, real time pricing, and critical peak rebates. It also includes direct load control programs which provide the ability for power companies to cycle air

conditioners and water heaters on and off during periods of peak demand in exchange for a financial incentive and lower electric bills.
The main purpose of this paper is survey and evaluation of the profit of the retailer of electricity market and maximizing it by considering TOU pricing and shifting loads of the customer (A form of load management that involves shifting from peak to off-peak periods. Examples are information programs that encourage customers to use storage water heating and storage space heating) and modeling the risk by related parameter like confidence level. The results are also analyzed in GAMS software.

LITERATURE REVIEW

Competition models have been introduced in many region of the world and will be introduced in another countries very soon in future [1,2]. In a retail competition model, an electricity market allows many participants including customers to compete with each other, through which monetary and environmental benefits can be obtained for customers and service providers of the market [3,4]. Paper [5] discuss some economic issues and models which are important to realize and manage the retail competition market, this paper conduct case studies on the open access and the distribution automation. In [6], profit and risk of a retailer company which are obtained from future contracts, call option and wholesale market are investigated simultaneously. In [7] all points, mechanisms and strategies of the power system based on forming the electricity market and presence of different actors in this market are investigated, the main objective of this article is to propose approaches for optimizing manufacturer's profit and optimizing social welfare of the consumer. In [8] paper presents a new stochastic multi-layer agent-based model to study the behavior of electricity market participants. The wholesale market players including renewable power producers are modeled in the first layer of the proposed multi-agent environment. The players optimize bidding/offering strategies to participate in the electricity markets. In the second layer, responsive customers including plug-in electric vehicle (PEV) owners and consumers who participate in demand response (DR) programs are modeled as independent agents. In [9] a dynamic energy management framework, based on highly resolved energy consumption models, is used to simulate automated residential demand response. The models estimate the residential demand using a novel bottom-up approach that quantifies consumer energy use behavior, thus providing an accurate estimation of the actual amount of controllable resources.

THEORETICAL BASIS OF RESEARCH

3-1 Retail Choice Outcomes

Retail choice appears to have the following impacts on innovative service offerings:
1) Retail choice is extending the market penetration of dynamic pricing programs that reflect power system conditions. All other things equal, this improves the efficiency of use of power system resources, lowers the average costs of producing power, and tends to improve resource adequacy.
2) Retail choice promotes renewable resources. To the extent that this raises the market penetration of intermittent resources such as wind and solar, it may raise resource adequacy issues because of the non-dispatchability of such resources.
3) Retail choice has a mixed record in promoting demand response.
4) Retail choice has not generally promoted smart metering.

3-2 Types of Open Electrical Energy Markets

Bilateral Trading: As its name implies, bilateral trading involves only two parties: a buyer and a seller. Participants thus enter into contracts without involvement, interference or facilitation from a third party. Depending on the amount of time available and the quantities to be traded, buyers and sellers will resort to different forms of bilateral trading like *Customized long-term contracts*, *Trading "over the counter"*, *Electronic trading*
The essential characteristic of these three forms of bilateral trading is that the price of each transaction is set independently by the parties involved. There is thus no "official" price [9-11].
Electricity pools: In the early days of the introduction of competition in electrical energy trading, bilateral trading was seen as too big a departure from the existing practice. Since electrical energy is pooled as it flows from the generators to the loads, it was felt that trading might as well be done in a centralized manner and involve all producers and consumers. Competitive electricity pools were thus created. Pools are a very unusual form of commodity trading but they have well-established roots in the operation of large power systems. In fact, some of the

competitive electricity pools currently in operation were developed on the basis of collaborative pools created by monopoly utility companies with adjacent service territories[11][12].

Comparison of pool and bilateral trading

Since both the pool and the bilateral models of electrical energy trading have been adopted for electricity markets, it is worth reviewing the perceived advantages and disadvantages of both approaches.

As mentioned above, a competitive electricity pool is often created on the basis of an existing cooperation agreement between various utilities. Its conversion to operation on a competitive basis will therefore be less of a revolution than the creation of a completely new structure. Some of the concerns that accompany the introduction of competition may be alleviated by the somewhat less radical nature of the change.

In particular, the public and the government are likely to have fewer concerns about the security of the electricity supply if the same organization remains in charge. A pool provides a much more centralized form of system management. Not only does it handle all the physical electrical energy transactions but it usually also assumes the responsibility for operating the transmission system. This combination of roles avoids the multiplication of organizations but makes it more difficult to distinguish between the various functions that need to be performed in an electricity market.

3-3 Influence of Demand Response programs

Most electricity customers see electricity rates that are based on average electricity costs and bear little relation to the true production costs of electricity as they vary over time. Demand response is a tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized.

• *Price-based demand response* such as real-time pricing (RTP), critical-peak pricing (CPP) and time-of use (TOU) tariffs, give customers time-varying rates that reflect the value and cost of electricity in different time periods. Armed with this information, customers tend to use less electricity at times when electricity prices are high. In this study we use TOU tariffs.

• *Incentive-based demand response programs* pay participating customers to reduce their loads at times requested by the program sponsor, triggered either by a grid reliability problem or high electricity prices.

3-3-1 The Benefits of Demand Response

Electricity production due to closer alignment between customers' electricity prices and the value they place on electricity. This increased efficiency creates a variety of benefits, which fall into four groups:

• *Participant financial benefits* are the bill savings and incentive payments earned by customers that adjust their electricity demand in response to time-varying electricity rates or incentive-based programs.

• *Market-wide financial benefits* are the lower wholesale market prices that result because demand response averts the need to use the most costly-to-run power plants during periods of otherwise high demand, driving production costs and prices down for all wholesale electricity purchasers. Over the longer term, sustained demand response lowers aggregate system capacity requirements, allowing load-serving entities (utilities and other retail suppliers) to purchase or build less new capacity. Eventually these savings may be passed onto most retail customers as bill savings[13].

• *Reliability benefits* are the operational security and adequacy savings that result because demand response lowers the likelihood and consequences of forced outages that impose financial costs and inconvenience on customers.

• *Market performance benefits* refer to demand response's value in mitigating suppliers' ability to exercise market power by raising power prices significantly above production costs [12-14].

3-4 Risk Modeling of the Problem

Conditional value at risk (CVaR) 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. Mathematically speaking, CVaR is derived by taking a weighted average between the value at risk and losses exceeding the value at risk. CVaR is also known as mean excess loss, mean shortfall, tail VaR, average value at risk or expected shortfall. CVaR was created to serve as an extension of value at risk (VaR). The VaR model allows managers to limit the likelihood of incurring losses caused by certain types of risk, but not all risks. In (1) & (2) the related equation of this modeling will be shown[11-13].

$$CVar = Maximize_{\xi,new} \quad \xi - \frac{1}{1-\alpha}\sum_{\omega=1}^{N}\pi_\omega u_\omega \quad (1)$$

$$\xi - \sum_{t=1}^{N_T}\left(\sum_{j=1}^{N_J} R_\omega\right) \le u_\omega, \forall\omega \quad (2)$$

$$u_\omega \ge 0, \ \forall\omega \quad (3)$$

PROBLEM FORMULATION AND RESEARCH METHODOLOGY

4-1 Expected Profit

Retailer's profit in the electricity market can be states as follows [12][13]:

Difference between the revenue obtained from selling electricity to customers and the companies' costs in Pool contracts and buying energy from bilateral contracts, therefore the final profits depends on random and stochastic prices of Pool and customers' demands [14-17]. Accordingly if we want to define the retailer's profit before load shifting, we have:

$$F_0 = \sum_{t=1}^{N_T}\sum_{j=1}^{N_J}\lambda_{jt}^{c}P_{jt}^{c}L_t^{C} - \sum_{b=1}^{N_B}\lambda_b^B P_b^B L_b^B$$

$$-\sum_{\omega=1}^{N_W}\sum_{t=1}^{N_T}\sum_{r\in\theta_{tr}}\pi_\omega\lambda_{r\omega}^{P}L_r^{P}\left(\sum_{j=1}^{N_J}P_{jt}^{C} - \sum_{b\in\Omega_{rb}}P_b^B\right) \quad (4)$$

Also we can define the retailer's profit after load shifting like below:

$$F_L = \sum_{\omega=1}^{N_W}\sum_{t=1}^{N_T}\sum_{j=1}^{N_J}\pi_\omega(\lambda_{jt}^{C} + \Delta\lambda_{jt}^{C})$$

$$\times(P_{jt}^{C} + \Delta P_{jt\omega}^{C})L_t^{C} - \sum_{b=1}^{N_B}\lambda_b^B P_b^B L_b^B + \sum_{\omega=1}^{N_W}\sum_{r=1}^{N_R}\pi_\omega\lambda_{r\omega}^{P}L_r^{P}\sum_{b\in\Omega_{rb}}P_b^B$$

$$-\sum_{\omega=1}^{N_W}\sum_{t=1}^{N_T}\sum_{r\in\theta_{tr}}\pi_\omega\lambda_{r\omega}^{P}L_r^{P}\sum_{j=1}^{N_j}(P_{jt}^{C} + \Delta P_{jt\omega}^{C}) \quad (5)$$

Now, defining the elasticity for the customer is essential:

$$E_{jt\omega} = \frac{-\Delta P_{jtw}^{C}/P_{jt}^{C}}{\Delta\lambda_{jt}^{C}/\lambda_{jt}^{C}} \quad (6)$$

The retailer must maximize the difference between F_L and F_0 that introduced as an ΔF:

$$\Delta F = \sum_{\omega=1}^{N_W}\sum_{t=1}^{N_T}\sum_{j=1}^{N_J}\pi_\omega(1 - E_{jt\omega})\Delta\lambda_{jt}^{c}P_{jt}^{c}L_t^{C} - \sum_{\omega=1}^{N_W}\sum_{t=1}^{N_T}\sum_{j=1}^{N_J}\pi_\omega\frac{E_{jt\omega}P_{jt}^{c}L_t^{C}}{\lambda_{jt}^{c}}(\Delta\lambda_{jt}^{c})^2$$

$$+\sum_{\omega=1}^{N_W}\sum_{t=1}^{N_T}\sum_{r\in\theta_{tr}}\sum_{j=1}^{N_J}\pi_\omega\frac{E_{jt\omega}P_{jt}^{c}}{\lambda_{jt}^{c}}L_r^{P}\lambda_{r\omega}^{P}\Delta\lambda_{jt}^{c} \quad (7)$$

4-2 Stochastic Modeling of the Problem

$$\underset{\Delta\lambda_{jt}^{C}\,\forall j,t,\xi,u_\omega\ \forall\omega}{Maximize} \quad \xi - \frac{1}{1-\alpha}\sum_{\omega=1}^{N_W}\pi_\omega u_\omega \quad (8)$$

$$-\sum_{\in\Lambda_{tm}}\frac{E_{jt\omega}P_{jt}^{c}L_t^{C}}{\lambda_{jt}^{c}}\Delta\lambda_{jt}^{c} = 0; \quad \forall j, \forall m, \forall\boldsymbol{\omega} \quad (9)$$

$$\sum_{t=1}^{N_T}(P_{jt}^{C} - \frac{E_{jt\omega}P_{jt}^{c}}{\lambda_{jt}^{c}}\Delta\lambda_{jt}^{c})L_t^{C}(\lambda_{jt}^{C} + \Delta\lambda_{jt}^{c})$$

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

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

- The objective function introduced in (8) contains CVaR of the profit at the confidence level α.
- Equation (9) describe that, energy consumed by each customer in a month could not be changed.
- Equation (10) imposes the demand ramp rate limits for per month (0≤ $a \le 1$).
- Constraints (12) state that the selling prices after modifications must be zero or positive.

4-2 Generating Scenarios

In stochastic programming models we always face the problem of how to represent the random variables. This is particularly difficult with multidimensional distributions. An example form of generating scenarios shown in figure (1), in this paper we consider 40 pool prices and generate these 40 scenarios besides generating 20 scenarios of elasticity for customers.

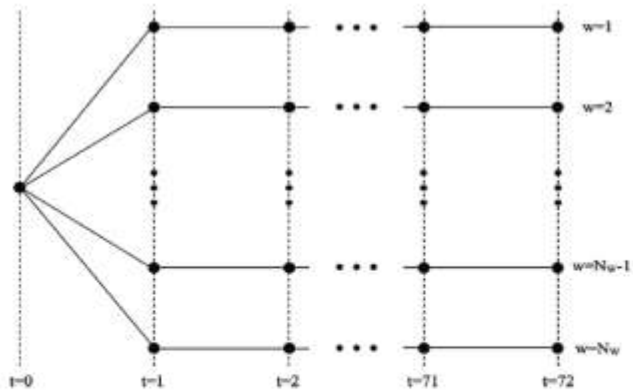

Fig (1) - heuristic procedure for scenario generation

CASE STUDY OF THE PROBLEM

We consider three groups of customers, residential, commercial and industrial; we aggregate pool prices in 6 periods with TOU tariffs, also bilateral contract between customers and retailer studied for 1 month. Number of customers are 100. 84 customers are residential, 12 of them are residential and 4 of them are industrial.
The consumption of per customer in peak and off-peak periods shows in table (1):

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Table (1) - power consumption of customers

Consumption in off-peak periods(kw)	Consumption in peak periods(kw)	Customer
2.9	3.6	84 residential
49	60	12 commercial
2000	3300	4 industrial

Table (2)- presents selling price of peak and off-peak periods:

Selling price in off-Peak periods (€/MWh)	Selling price in Peak periods (€/MWh)	Customer
88	94	Residential
82	88	Commercial
73	80	Industrial

Also we consider 75(€/MWh) for 7 MWh for the bilateral contracts.

RESULTS & SIMULATION

By considering equation (4)-(11) and solving the stochastic problem we can observe the price variation in order to encourage customers to shift their loads. The problem solved by GAMS software Using MINOS solver [18].
Figure (2) shows the price variation for peak periods and figure (3) shows the price variation for off-peak periods.
The retailer of the electricity market will increase the prices in peak periods while decreases the prices in off-peak periods, also the price variation depend on the elasticity of the customers. It means that the price variations are higher for the customers that have lower elasticity.

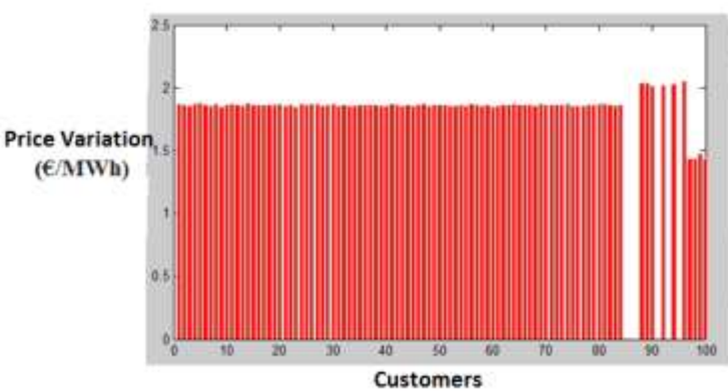

Fig (1) - price variations for peak periods

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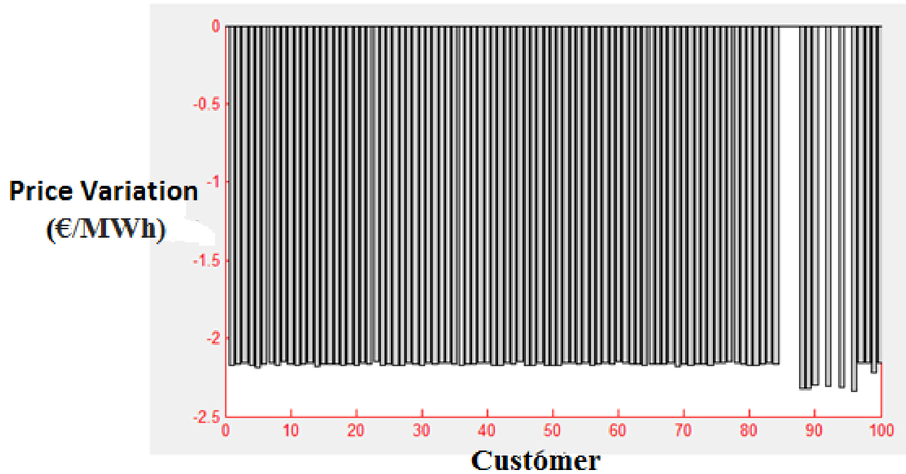


Fig (2) - price variations for off-peak periods

In the following the power variations for the customers in peak and off-peak periods showed in figure (3) & (4):

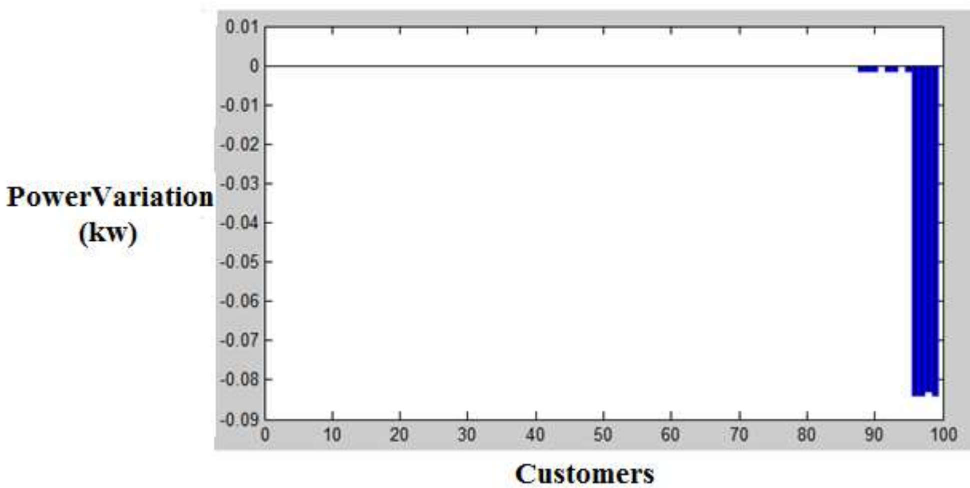


Fig (3) - power variation for peak periods

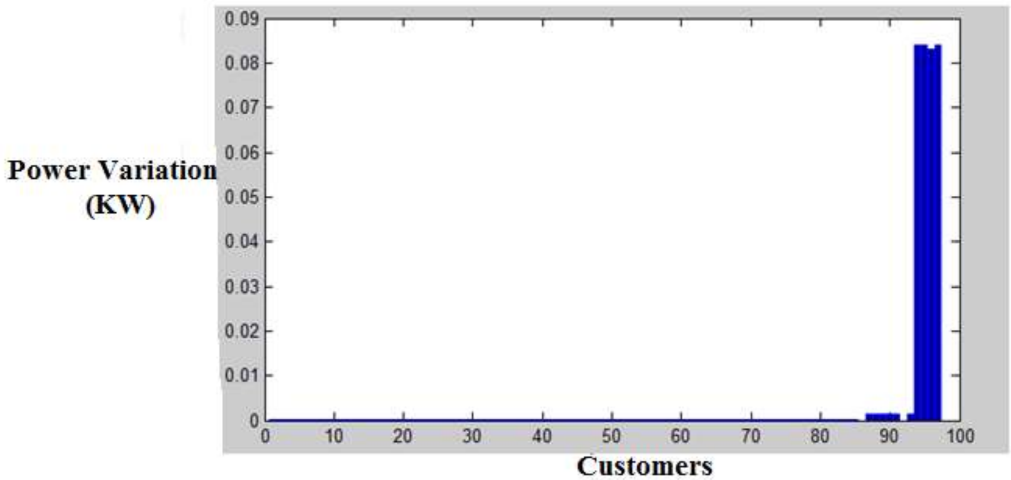
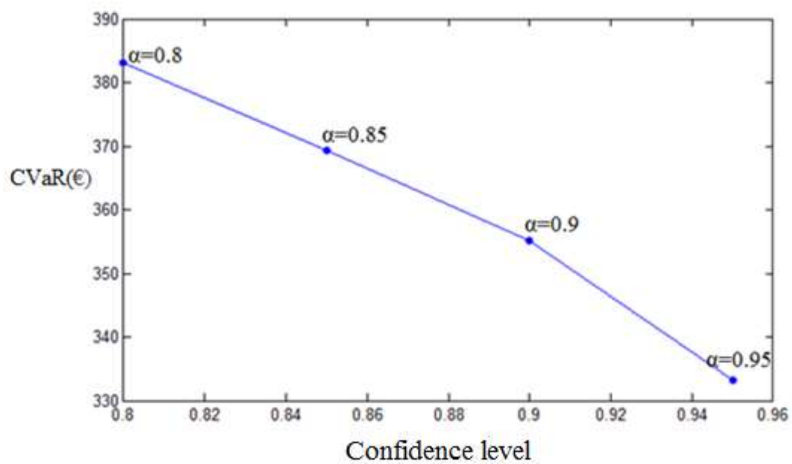


Fig (4) - power variation for off-peak periods

For the fig (3) & (4) that show the power variation: power variation for each customers depends on the elasticity that influenced by uncertainty of the problem which modeled with 20 scenarios of elasticity. By fig (3) & fig (4) we can observe that in peak periods power variations are the lowest for industrial customers while the power variations are the highest for this customer in off-peak periods.
Fig (5) & fig (6) presents the changes of CVaR and Expected profit of the retailer versus the confidence level (α): By increasing the confidence level, CVaR of the profit and Expected profit of the retailer decreases, by decreasing the expected profit and increasing the confidence level, energy price that imposed by the retailer will be low, and therefore load shifting by customer will be decrease.



Fig(5) - CVaR versus confidence level

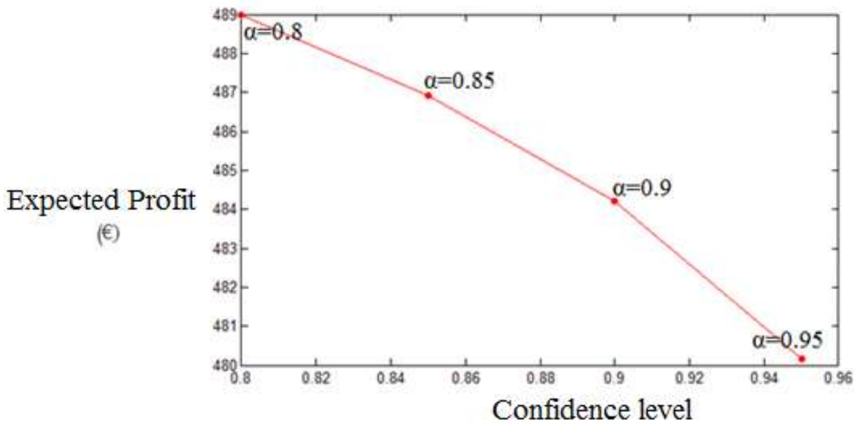


Fig (6) - Expected Profit versus confidence level

Table (3) shows the changes of CVaR and expected profit of the retailer for different values of α.

Table (3)-CVaR and expected profit of the retailer

Expected Profit	CVaR	α
488.9784	383.0293	0.8
486.9314	369.2827	0.85
484.1986	355.1922	0.9
480.172	333.2828	0.95

SYMBOLS USED IN PAPER

The symbols Used throughout retailer's problem in this paper are:

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_t^C = 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_{jt}^c= the power contracted in period t for customer j
λ_{jt}^c= Price of the energy for customer j in period t
λ_b^B= Price of the bilateral contracts in time period b
$\lambda_{r\omega}^P$= Price of the pool in time period r and scenario $\boldsymbol{\omega}$
ξ = Auxiliary variable used to calculate the CVaR ($).
μ_ω = Auxiliary variable related to scenario ω used to calculate the CVaR ($).
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

CONCLUSION

This paper has proposed a stochastic programming model that allows an electricity retailer to set the prices and offer optimal selling these prices to clients. To procure the electric energy to be sold to its clients, a retailer copes with two main challenges: while buying, it faces uncertain pool prices; while selling, it faces the uncertainty of client demand and the fact that clients may select a different retailer if selling prices are not competitive enough. The risk-aversion modeling is based on the CVaR. By this model in this paper the customers will encourage to shift their loads from peak periods to off-peak periods by considering TOU tariffs, in this way the retailer is interested in adapting the customer's consumption with its energy availability, reducing the energy bought in the pool-based electricity market. In the final, if this model performs in a good way, besides increasing the profit of the retailer, the payment of the customer will decrease and getting to the social welfare in electricity market will be easy.
For the future research we can use the role of wholesalers in electricity market and program the relation between wholesalers and retailers and customers to get the optimal point of the problem. Also this research can be examined in a system using DISTRIBUTED GENERATION regarding to renewable energy resources; by this situation we can analyze the profit of the retailer and payment of the customers.

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