A Solution for Risk Management of a Distribution Company in the Retail Market

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ABSTRACT:
In this paper, distributed generations for risk management of a distribution company (DisCo) in the competitive market environment are introduced. The proposed model for this problem considers a stochastic programming framework in the yearly horizon that is to maximize the expected profit considering the uncertainties of the retail market such as the end user demand and the electricity pool price. In this study, the key point is modeling the uncertainties of distributed generations as a reliable source for DisCos. Finally, the approach suggests the optimal resources for procuring the customers' load. Also a basic carbon market is modeled to support the role of renewable energies.

KEYWORDS: Distributed Generation, Distribution Company, Retail Market, Risk, Stochastic Programming.

1. INTRODUCTION

Traditionally, a distribution company (Disco) purchases energy from wholesale market, at a high voltage level, and then transfers this energy to final customers. Nevertheless, the restructuring process of the energy sector has stimulated the introduction of new agents and products, and the unbundling of traditional Disco into technical and commercial tasks, including the provision of ancillary services [1].

Customers demand and pool price have fluctuation and are uncertain. Therefore, the distribution company must consider these uncertainties. The stochastic programming methods [2] allow the company to maximize its profit at a risk level of profit variability. In [3] and [4], for electricity procurement, risk is considered. Reference [5] provides an overview of risk assessment tools in electricity markets, including appropriate tools to analyze the retailer perspective.

Distribution company planners continually endeavor to develop new planning strategies for their network in order to serve the load growth and provide their customers with a reliable electricity supply. In the present days, competitive electricity market forces drive the disco planners to investigate the economical and technical feasibility of new capacity expansion alternatives such as Distributed generation (DG) [6], [7]. the task to determine the optimal size and sites of DG sources in power systems is not an easy one, due to a number of factors. Reference [8] categorizes and discusses the various existing approaches.

The potential development of DG is sustained in the following factors: increasing power quality requirements, avoiding or shifting investment in transmission lines and/or transformers, ohmic losses minimization, environmental protection, and existence of high energy prices at retail level [9]. In the electricity market, DGs are usually not under the control of the independent system operator (ISO), but bulk customers or Discos. In this paper, only those DGs controlled by Discos are studied.

A DG investment planning from the perspective of a Disco that minimizes its investment and operation costs is proposed in [10]. A static single-period energy acquisition market model with DGs and interruptible loads are presented in [11], while a multiperiod energy acquisition model in a day-ahead electricity market addressed in [12]. Reference [13] employs distributed resources in an aggregated model for a Disco to compete in the market while satisfying the internal demand. In [14], a risk-constrained stochastic programming framework to decide which forward contracts the retailer should sign and at which price it must sell electricity so that its expected profit is maximized at a given risk level is modeled. A stochastic programming framework for electricity procurement of a large consumer from several alternatives (pool market, bilateral contracts and self-production) is addressed in [15], [16]. A mathematical method based on mixed-integer stochastic programming to determine the optimal sale price of electricity to customers and the electricity procurement policy of a retailer for a specified period in proposed in [17].

2. FRAMEWORK AND FORMULATION

In this section, the framework for the problem and its formulation is presented.

2.1. Framework

The aim of this paper is to determine the best possible combination of electric energy sources for a distribution company in demand procurement. It is considered that the retail price to the consumers is yearly constant. In this model, a Disco can only purchase its electricity from pool market or procure it with self production. The planning horizon of the year has been divided into 12 monthly periods. It should be noted that the duration of each period is not the same. For example, January is 744 hours, while February is 672 hours. Hereinafter, the number of hours in period t denoted by dt_t.

Disco has to face two major difficulties in demand acquisition. While purchasing electric energy, it must cope with uncertain pool prices. While selling electricity, it should handle the uncertainty of the end-user demand. This paper proposes using DGs for risk reduction in a stochastic programming.

For scenario generating of uncertainty parameters, forecasting of the history data or the average of history data is used. Demand and pool price parameters are forecasted with time series [18]. The normal distribution with mean of forecasted curve and time dependent standard deviation is used for scenario generation to cover all plausible realizations of end user demand and pool price. This standard deviation logically indicates that the farther time periods are forecasted with less accuracy. The scenarios of gas price, wind speed and radiation are generated based on history data. In scenario generating method, we consider the average curve of these data as the mean, and the mean standard deviation of every month periods as curve variances; then utilize this mean and standard deviation for our normal distribution.

2.2. DG Investment

Fixed investment cost on DGs is apportioned and paid monthly; but in our problem it is considered at the end of the year.

Let F be the annual flow of revenues required to recover the investment, defined as [19]:

$$F = \frac{I_0 . r}{1 - \left(\frac{1}{1+r}\right)^t} \tag{1}$$

where I_0 is the initial investment, r is the discount rate, and t is the life time of DG units.

2.3. Gas Fired Distributed Generators

One of popular technologies of distributed generation is gas fired generators. For modeling these DGs, we consider their fixed and variable costs. In this paper fixed cost is divided into shares that are paid by disco yearly.

Variable cost of this type of generators is modeled as:

$$varcost_{gas_{t,s}} = \sum_{t \in T} P_{gas_{t,s}} .(C_{gas_{t,s}} + C_{v,gas}).dt_t \tag{2}$$

where $varcost_{gas_{t,s}}$ is variable cost of gas fired DG, $P_{gas_{t,s}}$ is active power generation of DG, $C_{gas_{t,s}}$, and $C_{v,gas}$ are gas price, and operation and maintenance (O&M) cost in *t*-th period and scenario *s* respectively. dt_t is duration of period *t*. The uncertain parameter of gas price is its major part. $P_{gas_{t,s}}$ is used, whereas the power balance constraint should be satisfied in each period and with every scenario. It appears in our model in order to consider its cost; however our aim is not the accurate determination of this variable.

2.4. Wind Turbines

The main element in this type of generators is that the wind speed for planning is not definite. In the other hand, the power generated by a wind turbine depends on uncertain parameter of wind speed. For simplicity, it is considered that the generator output only depends on wind speed, not its direction. For modeling, some kinds of wind turbines are chosen and their curves are accessed linearly. Then they are applied to objective function for optimal value determination.

In catalogues, a minimum speed (a) for turbine start up, and a nominal speed (b) in which turbine reaches its maximum output power are considered. Between these speeds, linear curve can be used truly. The output will be approximately set on zero under (a) speed, and maximum value over (b) speed until a threshold speed. After threshold speed, generator has no output. Considering the above assessments for every selected turbine, it is modeled as:

$$P_{wind_i} = \frac{P_{cap_{wind_i}}}{(a_i - b_i)}(W_{sp} - a_i) \tag{3}$$

where P_{wind_i} is the generated power of *i*-th wind turbine, $P_{cap_{wind_i}}$ is the capacity of *i*-th turbine and W_{sp} is the wind speed.

One example of linear approximated curve of wind turbine is illustrated in Fig. 1.

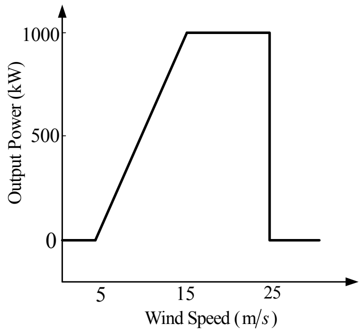

Fig. 1. Linear curve of wind turbine output

The operational power of *i*-th wind turbine considering above linear approximation is:

$$P_{wind_{t,s,i}} = \sum_{t \in T} \frac{P_{cap_{wind,i}}}{b_i - a_i} (W_{sp_{t,s}} - a_i).dt_t.C_{v,wind_i} \qquad (4)$$

where $P_{wind_{t,s,i}}$ is the operational power of *i*-th turbine and $W_{sp_{t,s}}$ is wind speed in *s*-th scenario and *t*-th period.

2.5. Solar Generation

The solar cell output power depends on solar radiation. The obtained power of each photovoltaic (PV) panel is related to some effective factors as below [20]:

$$P_{sol_{t,s}} = \tau_{t,s}.\cos\theta.\eta_m.A_p.\eta_p \qquad (5)$$

where $\tau_{t,s}$ is the solar radiation in w/m^2 with *s*-th scenario in *t*-th period, θ is angle of incidence, η_m is the efficiency of received radiation, A_p is area of PV panel in m^2 and η_p is the efficiency of PV panel.

PV panels contain some solar cells to make the facing area larger. For similar panels linear approximated relation between panel area and capacity can be considered. If Disco utilizes some specific available technologies of this kind for investment, the former approximation will be acceptable. Consequently, the operational power of PV panel is:

$$P_{sol_{t,s,j}} = \tau_{t,s}.\cos\theta.\eta_m.\alpha_j P_{cap_{sol_j}}.\eta_p \qquad (6)$$

Where α_j indicates the relation between the *j*-th panel capacity and its area. Also $P_{cap_{sol_j}}$ is capacity of *j*-th panel.

2.6. Formulation

In our problem, mathematical formulation for optimization contains 5 uncertain parameters. DGs that are modeled here include wind turbines, PV panels and small-scaled gas fired generators.

The objective function is maximizing the Disco expected profit (Profit= Revenue – Cost) that is:

$$EXP(profit) = \sum_{s \in S} \omega_s.prf_s \qquad (7)$$

where ω_s is the *s*-th scenario probability, prf_s is the yearly profit of company in *s*-th scenario that is modeled as:

$$\begin{aligned} prf_s = & \sum_{t \in T} [D_{t,s}.dt_t.prc + (P_{wind_{t,s}}.dt_t + P_{sol_{t,s}}.dt_t^{'}).prc_{clean}] \\ & - \sum_{t \in T} P_{net_{t,s}}.dt_t.prc_{net_{t,s}} \\ & - \sum_{f \in DG} \frac{P_{cap_f}.C_{fx_f}.r}{1 - \frac{1}{(1+r)^{k_f}}} \\ & - \sum_{t \in T} P_{gas_{t,s}}.(C_{gas_{t,s}} + C_{v,gas}).dt_t \\ & - \sum_{t \in T} P_{wind_{t,s}}.C_{v,wind}.dt_t \\ & - \sum_{t \in T} P_{sol_{t,s}}.C_{v,sol}.dt_t^{'} \end{aligned} \qquad (8)$$

Where $dt_t^{'}$ is duration of period *t* that related to average hours with solar radiation. $D_{t,s}$ is total end user demand, $P_{net_{t,s}}$ is power purchased from pool market in *t*-th period and scenario *s*. P_{cap_f} is capacity of *f*-th DG technology. C_{fx_f} is installation cost of *f*-th DG technology, prc is selling price settled by Disco to consumer in $\$/kWh$, prc_{clean} is price which is paid to clean energy for not producing emission gas, $prc_{net_{t,s}}$ is price of electricity in the pool during period *t* with scenario *s* in $\$/kWh$.

The proposed objective function includes both revenues and costs. The revenue contains two parts: the revenue of selling electricity to the customers, and the revenue of not producing pollutant gas with utilizing clean energy of wind and solar technology. The cost includes 3 parts: the cost of electricity purchasing from pool for demand procurement, the installation cost of DGs, and variable cost.

The variable cost of DGs operation is considered at final part of objective function. This cost for gas fired generators depends on uncertain parameter of gas price. Wind and solar systems are dependent on uncertain parameters of wind speed and radiation.

The above problem has some constraints as below:

2.6.1. Power Balance Constraints:

For demand procurement, the supplied power of both pool and self-production must be equal to the demand in each period and scenario:

$$D_{t,s} = P_{net_{t,s}} + P_{gas_{t,s}} + P_{wind_{t,s}} + P_{sol_{t,s}} \quad \forall t \in T, \forall s \in S \quad (9)$$

2.6.2. Constraints on DG Operation:

The power generated from DG must be less than the DG capacity in each period and scenario:

$$\begin{cases} P_{gas_{t,s}} \leq P_{cap_{gas}} \\ P_{wind_{t,s}} \leq P_{cap_{wind}} \\ P_{sol_{t,s}} \leq P_{cap_{sol}} \end{cases} \tag{10}$$

2.6.3. *Constraints on Demand Procurement from System:*

The total power delivered by the substation over the outgoing distribution feeders must be within the substation capacity limit:

$$P_{net_{t,s}} \leq P_{net_{\max}} \tag{11}$$

where $P_{net_{\max}}$ is substation capacity limit.

3. CASE STUDY

3.1. Data

The performance of the proposed methodology is illustrated through a realistic case study. A time series of six years from 2003 to 2008 is used to characterize the demand and pool price of the electricity market of mainland Spain [21].

The uncertainty of the end user demands is modeled through a set of five scenarios. Demand scenarios are generated by adding a random term to the expected demand of end user. The standard deviation of the random term increases with the time period. Fig. 2 depicts the demand for the five scenarios considered.

Pool price uncertainty is modeled through a 7 scenario set. Fig. 2 shows the pool prices in all of the 7 scenarios for the 12 periods considered. Likewise pool price scenarios are generated with a increasing random term.

Henry-Hub Index is used for natural gas spot price data of six years from 2003 to 2008 [22]. The averages of daily price data are considered in each month and the averages of these prices in similar months are computed during these years. The computed data with their standard deviation in a normal distribution are used to model gas price through a set of three scenarios. Fig. 2 shows the considered three scenarios of gas price.

Data history for wind speed of a wind farm in Spain is available in [23]. These data are in detail and have been classified hourly for five years from 2004 to 2008. Here the monthly averages of these years are computed. Based on these averages, considering their standard deviations with a normal distribution, the wind speed is modeled through a set of three scenarios. Fig. 2 illustrates the wind speed for the three scenarios considered.

The data of solar radiation are hardly available. Reference [24] shows some estimated data of solar radiation in different geographic areas. For considering the uncertainty of this parameter the estimated data are used. A normal distribution is used for scenario generating with the averages of these data and the standard deviations that are considered 0.2 of the averages. A set of three scenarios for solar radiation is depicted in Fig. 2.

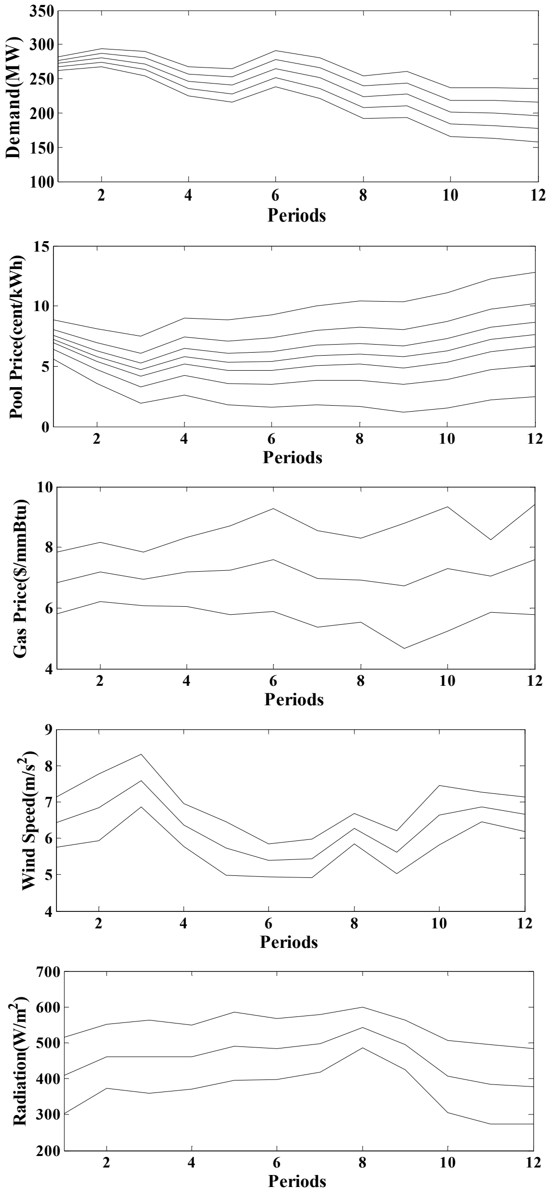

Fig. 2. Demand, Pool price, Gas price, Wind speed and Radiation scenarios.

A joint scenario tree of 945 scenarios is generated by taking into account each of 5 demand scenarios, 7 pool price scenarios and 3 scenarios for each of gas price, wind speed and solar radiation. Probability of each scenario for 5 uncertain parameters is provided in Table I. Note that the probability of each resulting scenario is equal to multiplication of demand, pool price, gas price, wind speed and solar radiation scenarios. In this way, the sum of the probabilities over all scenarios of the joint tree is equal to 1.

Table 1. Probability of each scenario for 5 uncertain parameters (%)

Uncertain parameters	Scenario number						
	1	2	3	4	5	6	7
demand	10	20	40	20	10	-	-
pool price	5	10	20	30	20	10	5
gas price	20	60	20	-	-	-	-
wind speed	20	60	20	-	-	-	-
radiation	25	50	25	-	-	-	-

3.2. Results

The resulting problem has been solved using CPLEX under GAMS [25].

The result (number of scenarios determined) can be verified using the central limit theorem (CLT). Based on CLT, if the number of scenarios is sufficiently large, then the sampling distribution of sample means is approximated by a normal distribution [26]. The distribution of sample means of profits for 945 scenarios is plotted in Fig. 3. As shown in Fig. 3, the probability density function is approximately close to normal distribution. Therefore, the number of scenarios (samples) is sufficiently large.

Fig. 4 illustrates the sensitivity of expected profit versus the volatility of uncertain parameters. In this figure, we simulated different levels of volatility with standard deviation changing. For sensitivity investigating, a volatility coefficient is used which is multiplied by the standard deviation of normal distribution. The proposed coefficient is assumed 0.5, 0.7, 1, 1.5 and 2. This coefficient for each of 5 uncertain parameters is considered separately. As it is shown in Fig. 4, the more demand and pool price volatility, the less expected profit, and volatility of gas price, wind speed and solar radiation does not have such a great influence on expected profit; which its reason can be the high price of their energy.

Fig. 5 depicts the cumulative distribution function of Disco profit with 945 scenarios. We calculated the Value at Risk (VaR) in different confidence levels with using this figure. These values are presented in table II. These confidence levels express the certainty criterion of VaR. A mathematical explanation of VaR that is used here is: profit related to expected profit [27]. Minus sign indicates the loss related to expected profit, while positive sign indicates benefit related to it. As table II shows clearly, in usual confidence level of 95% VaR will be -133*10^6 dollars. This means that with the probability of at least 95%, the loss related to expected profit is less than 133*10^6 dollars. This table proves that with confidence level decreasing or risk-taking increasing, the profit related to expected profit will increase.

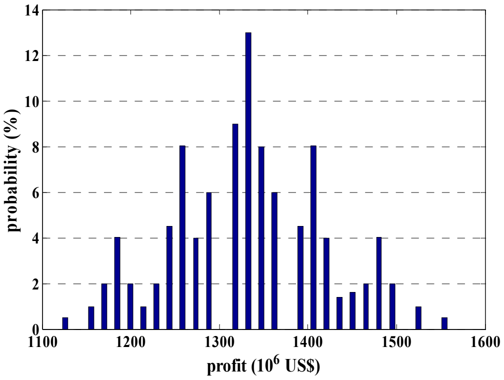

Fig. 3. The distribution of profit with 945 scenarios

Table 2. VaR in different confidence levels

Confidence level (%)	98	95	90	80	70	60	50
Profit (10^6 \$)	1159	1176	1207	1249	1276	1311	1325
VaR (10^6 \$)	-150	-133	-102	-60	-33	2	16

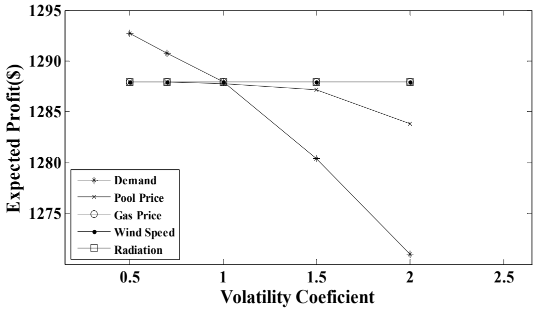

Fig. 4. Sensitivity of expected profit

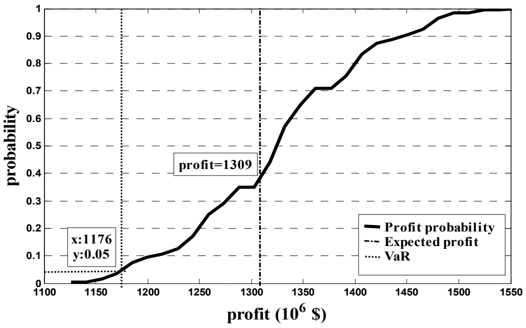

Fig. 5. Cumulative distribution function of profit

4. CONCLUSION

This paper provides a stochastic programming methodology with considering demand and pool price uncertainties that allows a distribution company to engage in medium-term. The target is maximizing the expected profit for the Disco. This approach arrives at the optimal feasible DG investment plan under uncertainty of gas price, wind speed and solar radiation for gas fired DG, wind turbine generator and photovoltaic (PV) panel, respectively. The proposed linear formulation proves both efficient and robust as demonstrate via a real case study. Sensitivity and VaR analysis on numerical results is presented. Finally, we are currently investigating novel models based on distributed resource (DR) programs and new forward contracts with the purpose of exploring these objects on expected profit and risk analysis.

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