A DECISION SUPPORT SYSTEM FOR OPTIMAL ENERGY SOURCING IN LIBERALISED ENERGY MARKETS

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ABSTRACT

In liberalised energy markets it could be very important for users to decide how to acquire energy among different transaction markets in order to minimize the supply costs with relatively low risk. To address this problem the paper proposes the employment of a solution methodology based on the Decision Theory. Thanks to the adoption of this methodology users can identify the optimal energy sourcing mix among different transaction markets which minimizes the expected supply costs and the related risks. The effectiveness of the proposed methodology has been demonstrated for a real medium size user based on the actual data of the Italian power market for a 4 months time scenario.

INTRODUCTION

The advent of the liberalized electricity markets has led to a sensible revision of the principles and the guidelines that end users should adopt in defining effective energy sourcing policies [1]. The new competitive scenario has sensibly affected the medium and small users which were traditional served by blinded tariffs. These users can take advantage of the liberalised energy market by acquiring the electrical energy necessary to satisfy their load profiles among different transaction markets (i.e. by stipulating bilateral contracts and/or by participating to the spot market).

In addressing this issue users should take into account explicitly both the market risks and the energy demand prediction errors. Market risks are mainly due to the energy costs dynamics. In the spot market the energy costs depend by the specific market structure and are typically characterised by high volatility. In a bilateral market the price is determined by the parties involved (although it may also depend on the spot prices, especially in a market environment where spot market and bilateral trading co-exist [2]).

Further risks are induced by the user energy demand fluctuations. Since energy sourcing is based on programmed energy load profiles (predicted from one to several day ahead) the corresponding forecasting errors introduces further sources of uncertainty in optimal energy sourcing assessment.

In this complex scenario, effective tools aimed at supporting users in acquiring electrical energy among different transaction markets by minimizing the supply costs with relatively low risks are strongly necessary. This problem falls within the area of “decision making under risk” and can be effectively addressed by using settled risk analysis based solution strategies widely explored in the power economy literature [3-8].

In particular paper [3] proposes the employment of fuzzy adaptive particle swarm optimization to address an optimal bidding strategy of a thermal generator in a uniform price spot market considering a precise model of nonlinear operating cost function and minimum up/down constraints of unit commitment.

In paper [4], a midterm power portfolio optimization problem supporting a Load Serving Entity to serve its load, maximize its profit, and manage its risks is presented.

The paper [5] proposes a sequential optimization approach based on the mean-variance portfolio theory that allows Generations Company’s to decide the trading proportion of spot and contract markets in order to maximize their profit and minimize the associated risk.

Paper [6] presents a methodology for mid-term risk management of a power portfolio, which includes generation assets and energy contracts and considers explicitly all technical constraints.

Paper [7] proposed new contract decision making algorithms for bidding, pricing and risk assessment in liberalised energy markets. Bidding decision in spot markets is formulated as a Markov Decision Process that can be used to determine the price and amount of electricity for a supplier. Pricing in a bilateral market is calculated using the no-arbitrage principle and stochastic optimization.

In paper [8] the bidding decision making problem is studied from a supplier’s viewpoint in a spot market environment. The decision-making problem is formulated as a Markov Decision Process. A risk-neutral decision-maker is assumed, the optimal strategy is calculated to maximize the expected reward over a planning horizon.

The application of these methodologies allows generation companies to make a trading plan before bidding into spot markets to get an expected high profit. This raises the competitiveness between the generation companies with indirect benefits also for the users. Anyway these papers propose effective solutions for risk management in liberalised electricity markets mainly from a supplier’s viewpoint. The application of these tools in supporting user energy sourcing policies is not straightforward and requires further investigations.

In order to try and address this issue this paper proposes a novel strategy for the solution of the energy sourcing problem from an user perspective.

To this aim, two energy transaction markets are considered: spot and bilateral contract market. An energy sourcing approach is established based on the decision theory (a body of knowledge and related analytical techniques designed to help a decision maker choose among a set of alternatives in light of their possible consequences and in the presence of uncertainty). The solution for the optimal allocation is derived with given bilateral contract prices and statistical characteristics of both the spot market prices and the user
load. The effectiveness of the proposed methodology has been demonstrated for a typical medium size user based on the actual data of the Italian power market for a 4 months period.

ELEMENTS OF DECISION ANALYSIS

Decision Analysis is a set of systematic methodologies aimed at supporting a decision maker (i.e. individuals or organizations) in solving complex decision problems in a formal manner.

Typically the decision problem can be formalized, quite apart from the specific applicative context, as the problem of choosing from a set of mutually exclusive alternatives the one which is optimal in some sense. Frequently, due to the lack of precise knowledge about the alternative consequences, some elements of decision process may not be uniquely assessed, then introducing a lack of determinism in the problem solution. Uncertainties in decision analysis stem from the unpredictable states of nature which cannot be influenced by the decision maker and whose occurrence is often probabilistic in nature [9]. The states of nature can be modelled by defining the most relevant “scenarios” which influence the consequences of the different alternatives. Each scenario is characterised by (i) a combination of values for the state variables descriptive of the problem under study and (ii) its respective probability. The decision problem is solved assuming the hypothesis that the “true” state of nature is amongst the relevant scenarios identified [9,10].

Once the alternatives open to the decision-maker and the relevant scenarios have been defined, they can be arranged in a “Decision Matrix” containing the outcomes of each alternative for the various scenario. In particular, given a set of \( N \) mutually exclusive alternatives:

\[
\Lambda = (a_1, ..., a_m, a_n) \quad (1)
\]

and a set of \( M \) exhaustive and mutually exclusive scenarios:

\[
\Pi = (s_1, ..., s_m, s_n) \quad \text{s.t.} \quad \forall i, j \in \{1, ..., m\} \quad s_i \cap s_j = 0 \quad \text{and} \quad \bigcup_{j=1}^{n} s_j = 1 \quad (2)
\]

the decision matrix \( D \) can be defined as:

\[
D = \begin{bmatrix}
d_{11} & \cdots & d_{1n} \\
\vdots & \ddots & \vdots \\
d_{m1} & \cdots & d_{mn}
\end{bmatrix} \quad (3)
\]

where the generic element \( d_{ij} \) of the decision matrix represents the outcome (a.k.a. payoff) of the alternative \( a_i \) when the scenario \( s_j \) occurs.

The decision problem can now be solved by identifying the row vector of the decision matrix which is optimal in some sense.

To address this issue the overall value of each row vector (i.e. the overall value of each alternative under the various scenarios) should be assessed a valuation function (i.e. a suitable real-valued function defined on the set of all row vectors of the decision matrix):

\[
V : \text{Rows}(D) \rightarrow \mathbb{R} \quad (4)
\]

A typical paradigm frequently adopted in defining the valuation function is the expected monetary value. According to this paradigm the function \( V \) assumes the following structure:

\[
V(a_i) = V(d_{i1}, ..., d_{in}) = \sum_{j=1}^{n} p_j d_{ij} \quad (5)
\]

where \( p_j \) denotes the probability of the scenario \( s_j \) while \( V(a_i) \) represents the mean of the random payoff when the alternative \( a_i \) is chosen.

In this case the solution of the decision problem is the alternative \( a_{opt} \) which maximizes the expected monetary value:

\[
a_{opt} = \{ a_i, i^* = \text{argmax} V(a_i) \} \quad (6)
\]

A further strategy that could be applied to solve a decision problem is to define the so called “Regret Matrix” [10]. The elements \( r_{ij} \) of this matrix can be obtained by following these steps:

Identify for each scenario (i.e. for each column of the decision matrix) the maximal payoff:

\[
M_j = \max_{i=1,...,m} d_{ij} \quad (7)
\]

Calculate the “regret” of having selected the other alternatives if the scenario \( s_j \) indeed occurred weighted by the scenario probability:

\[
r_j = (M_j - d_{ij})p_j \quad (8)
\]

Once the regret matrix has been calculated, the decision problem can be solved by applying the minimax regret rule (i.e. by selecting the alternative for which the maximum regret is as small as possible):

\[
a_{opt} = \{ a_i, i^* = \text{argmin} \{ r_j \} \} \quad (9)
\]

SOLVING THE ENERGY SOURCING PROBLEM BY DECISION ANALYSIS

Decision analysis could represent an useful supporting tool in solving the problem of energy sourcing in a liberalized market from an user perspective. In this scenario the analyst should identify day by day (from one to several day ahead) the optimal energy sourcing mix between the spot market and the bilateral contracts which minimizes the expected supply costs. In addressing this issue he/she should take into account explicitly both the market risks (i.e. fuel price volatility, electricity price volatility, etc.) and the energy demand prediction errors (i.e. daily load volatility).

This problem falls within the area of “decision making under risk” and can be effectively solved by decision
analysis.

The application of decision analysis to the problem under study asks for the definition of the set of mutually exclusive alternatives (i.e. one for each possible energy sourcing mix). Then the states of nature should be modelled by defining the most relevant “scenarios” which influence the consequences of the different alternatives.

In this connection the effect of spot market volatility and load prediction error could be considered as the primary sources of uncertainty introducing a lack of determinism in the problem solution. The statistical correlation between the bilateral contract and the spot market prices represents another important source of uncertainty. This complex issue has not been addressed in this study since it is currently under investigation by the authors.

Consequently the $i$–th scenario is described by:

$$s_i = \{p_{-m}^{SM} \leq p_{-m}^{SM} \leq p_{-m}^{SM}, E_{-m}^{D} \leq E_{-m}^{D} \}$$  \hspace{1cm} (10)

Where $p_{-m}^{SM}$ is the spot market hourly energy price, $E_{-m}^{D}$ is the hourly electrical energy demand, while $\{p_{-m}^{SM}, E_{-m}^{D} \}$ and $\{E_{-m}^{D}, E_{-m}^{D} \}$ represent, respectively, the minimum and maximum values of $p_{-m}^{SM}$ and $E_{-m}^{D}$ corresponding to the $i$–th scenario.

The statistical characterisation of $p_{-m}^{SM}$ and $E_{-m}^{D}$ based on the analysis of their historical trends leads to calculate the corresponding scenario probabilities:

$$p_i = P(s_i) = P\{p_{-m}^{SM} \leq p_{-m}^{SM} \leq p_{-m}^{SM} \} \cap \{E_{-m}^{D} \leq E_{-m}^{D} \}$$  \hspace{1cm} (11)

The optimal alternative can then be identified by applying one of the solution strategy described in the previous section.

CASE STUDY

This section assesses the proposed methodology in the task of defining optimal energy sourcing policies for a medium size Hospital located in the south of Italy and characterised by an electrical power installed of 500kW.

This user has stipulated a bilateral contract characterized by the data summarized in Table I. It has been assumed that (i) the user can access to the day-ahead electricity market by submitting hourly bids with no price indication; (ii) there is no correlation between the bilateral contract price (that has been assumed fixed) and the spot market price.

As far as the energy demand volatility is concerned, an adaptive local learning based algorithm has been applied for the day ahead load forecasting. The application of this advanced algorithm leads to predict accurately the energy demand. Consequently, the effect of load volatility has been neglected in this simulation study.

The simulation session is focused on a 4 month scenario (from April to July 2006). The real spot market price evolution of the Italian electricity market, which is uniform on the entire national territory, has been considered.

### Table I: Electrical energy costs of the bilateral contract

<table>
<thead>
<tr>
<th>Days</th>
<th>Hour</th>
<th>Energy price [€/MWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Working days (Monday-Friday)</td>
<td>9&lt;(t)&lt;12 am</td>
<td>120</td>
</tr>
<tr>
<td></td>
<td>1 pm</td>
<td>80</td>
</tr>
<tr>
<td></td>
<td>From 2 to 5 pm</td>
<td>120</td>
</tr>
<tr>
<td></td>
<td>From 6 to 9 pm</td>
<td>80</td>
</tr>
<tr>
<td></td>
<td>From 10 pm to 9 am</td>
<td>60</td>
</tr>
<tr>
<td>Non working days</td>
<td>Entire day</td>
<td>60</td>
</tr>
</tbody>
</table>

The solution of the sourcing problem asks for the assessment of the optimal allocation of the user energy demand for each hour of the next day between the bilateral contract $E^{BC}$ and the spot market $E^{SM}$. To solve this problem we define, for each hour of the next day, the following set of decision alternatives:

$$a_i = \{E^{SM} = 0 \cdot E^{D}, E^{BC} = 1 \cdot E^{D} \}$$

$$a_i = \{E^{SM} = 0.1 \cdot E^{D}, E^{BC} = 0.9 \cdot E^{D} \}$$

$$a_i = \{E^{SM} = 0.2 \cdot E^{D}, E^{BC} = 0.8 \cdot E^{D} \}$$

.....

$$a_i = \{E^{SM} = 1 \cdot E^{D}, E^{BC} = 0 \cdot E^{D} \}$$

As far as the definition of the “states of nature” is concerned, two different strategies could be adopted. The first one is based on the statistical characterization of the hourly energy spot market price which allows us to statistically characterize the “price scenarios”. This strategy is refereed as “direct approach”.

The second one is based on the adoption of a price forecasting algorithm and on the statistical characterization of its prediction error. This strategy is refereed as “indirect approach”.

Both of these strategies try to statistically characterize a random variable that influence the payoff of the decision alternatives. For the “direct approach” the random variable is the spot market price while, for the “indirect approach”, it is the price forecasting error $e$. Detailed studies developed by the authors have shown that the “indirect approach” leads to more robust results and it has been adopted in this simulation session. As far as the one day ahead price forecasting is concerned, the algorithm proposed in [11] has been adopted.

The state of nature can be characterized by defining the following scenarios:

$$s_1 = (e < -0.1)$$

$$s_2 = (-0.10 \leq e \leq -0.9)$$

$$s_3 = (-0.9 < e \leq -0.8)$$

.....

$$s_{21} = (0.9 \leq e \leq 0.1)$$

$$s_{22} = (e > 0.1)$$

In order to identify the optimal alternative the selecting
criteria analyzed in section 2 have been tested. The better performances have been obtained by applying the “minimax” regret rule.

The corresponding results are shown in fig. 1-2.

In details fig. 1 reports the profile of the percentage daily energy supply saving obtained by applying the proposed methodology compared to a sourcing policy based exclusively on the bilateral contract. The total saving obtained on the analysed time period is of the order of 15% (more than 10k€).

Fig. 2 reports the detail of the sourcing policy identified for a particular day (characterised by a high spot market price volatility).

Analysing this figure it is worth to note as the proposed method allows the user to manage effectively the hourly spot market price volatility. In fact it suggests to acquire much energy on the spot market from 15 to 20 and to sensibly reduce it from 10 to 13 (where the spot market prices are expected to be higher). The mean supply saving for this day is of the order of 17%.

Figure 2: Daily sourcing policy identified by the proposed methodology:

a) Energy profiles
b) Hourly energy price
c) Hourly supply cost

4.0 Conclusions

Users can take advantage of the liberalised energy market by acquiring the electrical energy necessary to satisfy their load profiles by stipulating bilateral contracts and/or by participating to the spot market. In addressing this issue they should take into account explicitly both the market risks (i.e. price volatility) and the energy demand prediction errors (i.e. load volatility). To try and solve this problem the paper proposed the employment of a Decision Analysis based methodology.

Thanks to the adoption of this methodology users can identify day by day the optimal energy sourcing mix among different transaction markets which minimizes the expected supply costs and the related risks. The simulation results, obtained on a real case study, have demonstrated that the application of the proposed method allows the user to manage effectively the hourly spot market price volatility obtaining reasonable supply cost savings compared to
sourcing policies based exclusively on bilateral contracts.

REFERENCES