
Mansour Charwand, Abdollah Ahmadi, Ali Reza Heidari, Student Member, IEEE, and Ali Esmaeel Nezhad

Abstract—In midterm planning, the objective of an electricity retailer is to manage a portfolio of different contracts and determine the selling price offered to its clients. Assuming that, within an electricity market framework, rival retailers compete for prices in order to achieve the largest possible number of clients. In addition, the reasonable criterion for the retailer is to select a solution that attains the minimum selling prices while satisfying the constraints. The proposed framework in this paper is modeled in the form of a multiobjective framework to simultaneously maximize retailers’ profit and minimize selling prices to clients. The normal boundary intersection method is implemented to generate Pareto-optimal solutions. The best compromise solution is adopted using a fuzzy decision maker. Roulette wheel mechanism and scenario generation wherein the stochastic optimization problem is converted into its respective deterministic equivalents. Benders decomposition has been employed as a robust algorithm to reach the optimal solution. The efficiency of the presented method is verified by making a comparison of its performance with another multiobjective optimization method through a real case study to show its superiority.

Index Terms—Benders decomposition, electricity retailer, fuzzy decision maker, multiobjective mathematical programming (MMP), normal boundary intersection (NBI) method.

NOMENCLATURE

Sets

- \( t \) Set of time periods.
- \( S \) Number of scenarios.
- \( I \) Number of blocks in the price–quota curves.
- \( F \) Number of forward contracts.
- \( J \) Number of power blocks in the forward contracting curves.
- \( L \) Number of client groups.
- \( E_R(l, i, t, s) \) Energy associated with block \( i \) of the price–quota curve of client group \( l \) in period \( t \) and scenario \( s \) (MWh).
- \( \bar{p}_R(l, i) \) Upper limit of the price in block \( i \) of the price–quota curve pertaining to the client group \( l \) (€/MWh).
- \( P^F(f, j) \) Upper limit of the power contracted from block \( j \) pertaining to the forward contracting curve of forward contract \( f \) (MW).
- \( \rho^F(f, j) \) Price of block \( j \) pertaining to the forward contracting curve of forward contract \( f \) (€/MWh).
- \( \pi(s) \) Probability of a scenario.
- \( \mu_l^i \) Membership function expressing the degree of optimality for the \( i \)th objective function in the \( r \)th Pareto-optimal solution.

Variables

- \( C^P(t, s) \) Cost of purchasing from forward contracts in each period (€).
- \( C^F(t, s) \) Net cost of trading in the pool in period \( t \) and scenario \( s \) (€).
- \( \text{IN}_R(l, t, s) \) Revenue obtained by the retailer from selling to client group \( l \) in period \( t \) and scenario \( s \) (€).
- \( P^F(f) \) Power purchased from contract \( f \) (MW).
- \( P^F(f, j) \) Power purchased from the \( j \)th block of the forward contracting curve of contract \( f \) (MW).
- \( E^P(t, s) \) Energy traded in the pool in period \( t \) and scenario \( s \) (MWh).
- \( E_R(l, i, t, s) \) Energy supplied by the retailer to client group \( l \) in period \( t \) and scenario \( s \) (MWh).
- \( \rho^R(l, i) \) Price of the \( i \)th interval of the price–quota curve for client group \( l \) (€/MWh).
- \( \rho^R(l) \) Selling price settled by the retailer for client group \( l \) (€/MWh).
- \( A(l, i) \) Binary variable, which is equal to 1 if the selling price offered by the retailer to client group \( l \)
belongs to block $i$ of the price–quota curve, otherwise 0.

$\lambda^p$ Dual variables of inequalities in the feasible slave problem.

$\lambda^r$ Dual variables of inequalities in the infeasible slave problem.

$f^r_i$ Value of the $i$th objective function in the $r$th Pareto-optimal solution.

I. INTRODUCTION

A. Aim

Retail competition in electricity is the ability of a customer to choose a preferred retail supplier, so-called an Electricity Service Provider. That retail supplier or service provider has the right of access to the local distribution network to which the customer is connected. The supplier typically generates its own electricity or buys it from a generator or a trader or from an electricity pool. The supplier pays the relevant transmission and distribution charges, typically based on published, nondiscriminatory, and regulated terms. The supplier is typically responsible for meter reading, billing, collection, complaint handling, and, possibly, other services, as well as for setting its own retail price and other terms. Generally, retailers purchase the electricity to be supplied to their clients both through the pool and the future markets. The objective of the retailers is to maximize the profit obtained from selling to customers.

The retailer must cope with uncertain pool prices and client demands, as well as with the possibility that clients might choose a different supplier, if the selling price offered by the retailer is not sufficiently competitive. After deciding the future market involvement and selecting the selling price, the retailer must determine its purchases and sales in the pool [1]. In all previous works, the objective of the retailer is maximizing the profit. Assuming that, within an electricity market framework, rival retailers compete for prices in order to achieve the largest possible number of clients. The reasonable criterion for the retailer is to select a solution that attains the minimum selling prices while satisfying the constraints. Thus, in this paper, a multiobjective mathematical programming (MMP) model has been proposed for an electricity retailer that consists of retailer profit and selling prices and supply sources, including the pool and forward contracts. In fact, financial risk that would be faced by the retailer has been modeled with selling price offered by the retailer to different groups of customers with a second goal for objective function. The proposed framework is based on the mixed-integer programming (MIP) formulations, whereas Benders decomposition has been employed as a robust algorithm to decompose the problem into a master and a slave problem, which is coordinated through Benders cut in order to reach the joint optimal solution. Finally, the best compromise solution is adopted using a fuzzy decision maker.

B. Literature Review

Focusing on the wholesale side of the electricity market has been dealt in several papers, and some different methods have been addressed, but a few research works have addressed issues relating to retail electric power operations.

In [2], the optimal price calculation using different price strategies is discussed while the impact of the elasticity of customer demands is evaluated. Reference [3] provided a procedure to determine the optimal price and energy procurement by the retailer and incorporates an acceptance function for the modeling of customer behavior. References [4] and [5] both proposed a stochastic programming methodology to determine the optimal sale price from retailers to customers based on fixed pricing and the amounts of power purchased from the pool and forward contracts. In addition, strategies, such as call options and self-production facilities, are considered in [5]. Reference [6] addressed the complementary problem of determining optimal pool bidding strategies for a retailer. Market uncertainty due to the spot market price and retailer’s load has been analyzed in [7]. Recent activities of retail market in certain states in the U.S. have been described in [8]. Electricity procurement cost minimization for a local electricity distribution company (LED) is addressed in [9] using a mean-variance technique subject to a cost-exposure constraint from pool and bilateral contracts. Reference [10] has also solved the problem by considering the tolling agreement as another energy procurement resource. In [11], a theoretical framework is developed to determine which forward-contract purchase minimizes the expected procurement cost of an LED subject to a cost-exposure constraint. Electricity procurement by large consumers has been solved in [12] utilizing a mean-variance methodology in which both forecast and historical price data are used to construct the price covariance matrix. A methodology has been presented in [13] giving a range of bilateral quantity and associated price for a retailer to ensure risk-constrained payoff. The exercise has been carried out with a single retailer in the market and for a case with competition among two retailers. In [14], the financial risk associated with the market price uncertainty is modeled using expected downside risk. Reference [15] has developed a multistage stochastic optimization approach, which accounts for the uncertainties of both electricity prices and loads, allowing the specification of conditional-value-at-risk requirements to optimize hedging across intermediate stages in the planning horizons. Reference [16] has developed the idea presented in [4], in which the client’s response to the retailer prices and the competition among rival retailers have been explicitly taken into account by a bilevel programming model.

In the power system literature, multiobjective optimization techniques have been applied to a large range of problems. Various multiobjective optimization approaches have been utilized, e.g., the weighted sum method and the goal-attainment method [17], the ε-constrained method [18]–[20], and game theory [21]. In this paper, normal boundary intersection (NBI) method is applied to multiobjective optimization problem, which is superior compared with the most common multiobjective approaches [22]. In addition to the aforementioned issues, thus far, a few works have been reported on NBI method. Reference [23] presented NBI method to form the Pareto surface for power system multiobjective optimization problems. Reference [24] used NBI approach for generating Pareto optimal set to develop optimal bidding strategies.
C. Contributions of the Paper

There are various medium-term strategies that the retail company can select according to the market situation, competitor status, and its position. These strategies include the following: cost strategy, differentiation strategy, and focus strategy. In the cost strategy (or invasive strategy), retailers are looking to increase their market share and cost superiority over other competing companies. Important tools in implementing this policy are the price reduction of energy selling, new and exciting products, and advertising and marketing investment, as well as efficiency increment.

In differentiation strategy, the retailer offers unique services, which will create added value for clients. In the focus strategy (defensive strategy), the retailer focuses on a small and narrow part of the retail market and offers differentiated services and makes an added value to its clients in order to benefit from their loyalty and to provide services to them. Small companies often choose to take a defensive strategy because of their limited competitive facilities and resources. This is acceptable in the short term. With increasing competition, defensive strategies cause clients to decrease in the future and shrinking of the market unless using other competitive market advantages. One of the main tasks of the retail companies is to establish long- and medium-term strategies based on one of the aforementioned strategies. Now, in this paper, various strategies (offensive or defensive strategy) that the retailer may take have been modeled in terms of a multiobjective model and what have not been done in previous retail-related papers.

The main contributions of this work with respect to the earlier ones can be briefly summarized as follows.

1) A new stochastic medium-term multiobjective framework has been proposed for an electricity retailer, including competing objective functions such as expected value of the profit and selling prices.
2) Applying a bilevel procedure to solve the proposed stochastic multiobjective problem and obtaining the best compromise solution using the fuzzy decision making process.
3) At the first level, roulette wheel mechanism and lattice Monte Carlo simulation (LMCS) are employed for random scenario generation. Using the above procedure, the stochastic multiobjective problem is converted into corresponding deterministic problems.
4) MMP approach based on the NBI method is implemented to solve each deterministic scenario at the second level.
5) Applying Benders decomposition algorithm as a capable solution method to obtain global results of the retailer’s decision in the medium-term horizon and to reduce computational burden.

D. Paper Organization

The remainder of this paper is organized as follows: Section II presents characterization of the problem’s uncertainties and the formulation of decision-making problem faced by the retailer. The proposed solution approach for the MMP problem is addressed in Section III. In Section IV, the performance of the proposed methodology is illustrated through a realistic case study and thoroughly discussed. Section V provides some relevant conclusions.

II. Problem Description and Formulation

The main idea of this paper is to derive three items through medium-term horizon as forward contracting decisions, grid purchase, and selling price for a retailer. Moreover, it is assumed that selecting the forward contracting to include risk premiums and the selling price is performed at the beginning of the planning horizon. Transactions having done in the pool mainly depend upon the energy acquired from forward contracts once the planning horizon begins. The planning horizon comprises several time periods based on the times at which decisions are made. As some decisions are made on the basis of hourly level, an hourly framework has been adopted in this paper.

A. Uncertainty Characterization

The price and load forecast error are used in this paper to model the uncertainties corresponding to spot market price and load at each planning period (1 h) [25]. In order to exploit the discretized probability density function (pdf), numerous scenarios can be randomly generated. Lattice is an algorithm leading to better results compared with ordinary Monte Carlo simulation method as it is a method to generate low-discrepancy procedures. Thus, LMCS is employed in this paper to generate scenarios. Moreover, roulette wheel mechanism (see [14] and [26]) has been employed to generate scenarios pertaining to each period, since there are different levels of price/load forecast levels and their probability derived from the pdf. In this regard, the first step is normalizing the probabilities corresponding to different price/load forecast error levels so that their summation becomes unity. Afterward, normalized probabilities are used to fill the [0, 1] range. Then, LMCS is used to generate random numbers between 0 and 1. Each random number falls in the normalized probability range with regard to a price/load forecast level in the roulette wheel. The roulette wheel mechanism is used to choose the corresponding price/load forecast error level for the respective scenario. A scenario reduction method is employed in this paper inferring with a fewer number of scenarios and a fairly good estimation of the original system. In this paper, the scenario reduction technique attempts to omit scenarios owning very low probability and the ones that are similar.

B. Supply of Energy Resources for the Retailer

1) Forward Contract: Forward contract is a contract in which the sector is contractually obliged to sell or buy a specified amount of electricity energy at a predetermined price at a certain time in the future. This type of contract is used to encounter the risk caused by pool price volatility. Bargaining power performed by the retailer is clearly accepted in the suggested model through contracting curves. As performed in [4], the forward market prices are supposed to rise as the amount traded varies interpreting a price-maker retailer. Since forward
contract quantities are decision variables corresponding to the forward prices with these stepwise curves, the proposed model takes forward quantities and forward prices, simultaneously. The cost imposed by purchasing energy through forward contracts based on the forward contracting curves and faced by the retailer is as follows:

\[ C^F(t) = \sum_{f=1}^{F} \sum_{j=1}^{J} \rho^F(f, j) P^F(f, j) \quad \forall t \in T \]  

(1)

\[ 0 \leq P^F(f, j) \leq \bar{P}^F(f, j) \quad \forall f \in F; j \in J \]  

(2)

\[ P^F(f) = \sum_{j=1}^{J} P^F(f, j) \quad \forall f \in F. \]  

(3)

Equation (1) illustrates the energy purchasing cost based on the forward contracts. This cost depends upon the power and energy prices contracted in each block of the forward contracting curve. The nonnegativity of the purchased power and energy prices contracted in each block of the forward price–quota curve are declared via constraint (2). The amount of purchased powers added to each block consists in each block and its upper bound is declared via constraint (3).

2) Pool Market: In this paper, it is assumed that a specified amount of the electricity demanded by the retailer’s clients is supplied using pool market by the retailer. Nevertheless, the retailer is able to take part in the pool market to sell or buy energy, provided that it is profitable. The net cost of trading in the pool can be calculated as follows:

\[ C^P(t, s) = \rho^P(t, s) E^P(t, s) \quad \forall t \in T; s \in S. \]  

(4)

C. Demand Supplied by the Retailer

Generally, there are several types of load in the electricity market, such as residential, commercial, and industrial loads. It is supposed that the clients are flexible in the case of selling price offered, the retailer’s clients are denoted by \( \rho^R(l) \). Therefore, too high value of \( \rho^R(l) \) causes a client to reject its retailer. Based on the selling price offered, the retailer sets a quantity, i.e., \( E^R(l, t, s) \), in each period \( t \) from the total client demand of group \( l \) in scenario \( s \). According to the method used in [4], a relationship would be established between the price offered and the client's demand supplied by the retailer while it is modeled exploiting a stepwise price–quota curve. The amount of electricity that a number of clients tend to buy at a given price is concluded from the price–quota curve. Equation (5) states the price–quota curve for each client group in each period, i.e.,

\[ E^R(l, t, s) = \sum_{i=1}^{I} E^R(l, i, t, s) A(l, i) \quad \forall l \in L; t \in T; s \in S \]  

(5)

\[ \rho^R(l) = \sum_{i=1}^{I} \rho^R(l, i) \quad \forall l \in L \]  

(6)

\[ \bar{\rho}^R(l, i - 1) A(l, i) \leq \rho^R(l, i) \leq \bar{\rho}^R(l, i) A(l, i) \quad \forall l \in L; i \in I \]  

(7)

\[ \sum_{i=1}^{I} A(l, i) = 1 \quad \forall l \in L. \]  

(8)

It is demonstrated through (5)–(8) that the demand of each client group supplied by the retailer in each period and scenario, i.e., \( E^R(l, t, s) \), is a function of the selling price \( \rho^R(l) \). As illustrated in (5), the amount of energy demand supplied by the retailer is equal to the level of energy pertaining to the price–quota curve denoted by the binary variables \( A(l, i) \). The intervals of the price–quota curve related to the selling price \( \rho^R(l) \) (6)–(8) are identified by \( A(l, i) \), which is a set of binary variables.

Equation (9) indicates the electricity energy balance for a retailer in each period and scenario, i.e.,

\[ \sum_{i=1}^{I} \sum_{l=1}^{L} E^R(l, i, t, s) A(l, i) = E^P(t, s) \]  

\[ + \sum_{f=1}^{F} \sum_{j=1}^{J} P^F(f, j) \quad \forall t \in T; s \in S. \]  

(9)

On the basis of the stepwise price–quota curve, the income obtained from selling electricity to the customers is calculated as follows:

\[ \text{IN}^R(l, t, s) = \sum_{i=1}^{I} E^R(l, i, t, s) \rho^R(l, i) \quad \forall l \in L; t \in T; s \in S. \]  

(10)

III. PROPOSED MULTIOBJECTIVE PROBLEM

As demonstrated in [22] and [23], several advantages are obtained through the NBI method in comparison with common multiobjective approaches.

A. Proposed Optimization Formulation

Two objective functions are considered for the proposed multiobjective framework over the medium-term planning: the first one is maximizing the profit of the retailer, and the second one is minimizing the selling prices so that the maximum possible number of clients is achieved. Equations (11) and (12) indicate the first and second objective functions, respectively.

1) Maximize \( f_1 \): Profit

\[ \sum_{s=1}^{S} \pi(s) \sum_{i=1}^{T} \left( \sum_{l=1}^{L} \sum_{i=1}^{I} E^R(l, i, t, s) \rho^R(l, i) - \rho^P(t, s) E^P(t, s) \right) \]  

\[ - \sum_{f=1}^{F} \sum_{j=1}^{J} \rho^F(f, j) P^F(f, j) \right). \]  

(11)

2) Minimize \( f_2 \): Sum of selling prices

\[ \sum_{l=1}^{L} \sum_{i=1}^{I} \rho^R(l, i). \]  

(12)

The expected profit of the retailer is equal to the expected revenue derived from selling electricity to end users and pool minus the expected cost of purchasing electricity through the pool and forward contracts as (11). The sum of the selling prices

\[ \sum_{l=1}^{L} \sum_{i=1}^{I} \rho^R(l, i). \]  

(12)
offered by the retailer to each group of customers is indicated in (12). Furthermore, the proposed MMP problem is subjected to several constraints, as mentioned in the previous section.

B. NBI Method

The general form of a multiobjective optimization problem in mathematical terms can be stated as follows:

\[
\begin{align*}
\text{Min/Max} & \quad F(x) = \{f_1(x), f_2(x), \ldots, f_n(x)\} \\
\text{subject to} & \quad g(x) \leq 0, \quad h(x) = 0, \quad x \in C
\end{align*}
\]

where the vector of the decision variables is denoted by \(x\), and \(C\) is the feasible solution space obtained by the problem constraints. A point such as \(x^* \in C\) can be considered as the Pareto optimal (non-dominated) for MMP, provided that there is no \(x \in C\) such that \(f_k(x) \leq f_k(x^*)\), for all \(k = 1, 2, \ldots, n\), with at least one strict inequality.

The anchor point, i.e., \(f^*_k\), in this method is formed as the \(k\)th objective function, which is minimized independently. \(f^*_k\) denotes the individual minima of the \(k\)th objective function. The shadow minimum (utopia point) \(F^*\) is defined as the vector comprising the individual global minima pertaining to the objectives, i.e.,

\[
F^* = (f^*_1, f^*_2, \ldots, f^*_n)^T
\]

The convex hull of individual minima (CHIM) has the following interpretation: let \(x^*\) be the respective minimizer of \(f_k(x), k = 1, 2, \ldots, n\), for \(x \in C\). Let \(F^*_k = F(x^*_k), k = 1, 2, \ldots, n\) and \(\Phi\) be the \(n \times n\) matrix whose \(k\)th column is \(f^*_k - F^*\) (payoff matrix). Afterward, the set of points in \(R^n\) that are convex combinations of \(F^*_k - F^*\), i.e., \(\Phi \mu : \mu \in R^n, \sum_k \mu_k = 1, \mu_k \geq 0, k = 1, 2, \ldots, n\), is known as the CHIM. The set of obtainable objective vectors \(F(x) : x \in C\) is denoted by \(F\) so \(C\) is mapped onto \(F\) by \(F\). Objective space is defined as the space \(R^n\), including \(F\), \(\partial F\) is the boundary of \(F\). The part of \(\partial F\) comprising the Pareto optimal points is determined using NBI approach. The main idea of this approach is that a point on the portion of \(\partial F\), including the efficient points, is the one at the intersection between the boundary \(\partial F\) and the normal pointing toward the origin emerged from any point in the CHIM. If the tradeoff surface in the objective space is convex, this point is definitely a Pareto optimal point.

Assuming a convex weighting \(\mu\), \(\Phi \mu\) denotes a point in the CHIM. If \(\bar{n}\) denotes the unit normal to the CHIM simplex toward the origin, then \(\Phi \mu + A\bar{n}\) demonstrates the set of points on that normal. Eventually, the global solution of the following subproblem is defined as the intersection point of the normal and the boundary pertaining to \(F\) that is the closest to the origin, i.e.,

\[
(NBL_\mu) \quad \text{Max } A
\]

\[
\begin{align*}
\text{subject to} & \quad \Phi \mu + A\bar{n} = F(x) \\
g(x) \leq 0, \quad h(x) = 0, \quad x \in C.
\end{align*}
\]

The vector constraint \(\Phi \mu + A\bar{n} = F(x)\) guarantees the actual mapping of point \(x\) by \(F\) on the normal while the rest of the constraints ensure the feasibility of \(x\) with regard to the original problem. The first set of constraints must be \(\Phi \mu + A\bar{n} = F(x) - F^*\), if the shadow minimum \(F^*\) is not the origin. In the payoff matrix \(\Phi\), the \(k\)th column is clarified as \(\Phi(\cdot, k)\mu = F(x^*_k) - F^*\). As \(f_k(x^*_k) = f^*_k\), it is obvious that \(\Phi(k, k) = 0\). Furthermore, as \(x^*_k\) is the minimizer of \(f_k(x)\) over \(x, j = 1, 2, \ldots, n\), then \(\Phi(j, k) \geq 0, j \neq k\). A number of points on the boundary of \(F\) are derived by solving NBI, such that efficiently forming the Pareto front.

C. Solution Methodology Based on the Benders Decomposition

The stochastic multiobjective model corresponding to retailer’s activities is formulated as an MIP problem involving binary decision variables and continuous ones. Benders decomposition [27]–[29] is one of the most well-known robust techniques [30], [31] in optimization problems to solve large-scale MIP problems. In order to exploit the underlying problem structures for different optimization problems, Benders decomposition technique is prosperously applied. There are two levels included in the Benders partition algorithm, which is a decomposition technique as master and slave. This algorithm creates iterative sequences between these two levels to achieve the joint optimal solution.

The master program is an integer problem, and the slave is a linear problem. The lower bound solution of the master problem, i.e., \(z_{\text{lower}}\), may involve fewer constraints. Thus, first, the master problem is solved. The slave will examine the solution of the master problem to see if the solution satisfies the remaining constraints. If the slave is feasible, the upper bound solution of the original problem, i.e., \(z_{\text{upper}}\), will be calculated while forming a new objective function for the further optimization of the master problem solution. If the slave is infeasible, an infeasibility cut representing the least satisfied constraint will be introduced to the master problem. Then, a new lower bound solution of the original problem will be obtained by recalculating the master problem with more constraints. The final solution based on the Benders decomposition algorithm may require iterations between the master problem and the slave. When the upper bound and the lower bound are sufficiently close, the optimal solution of the original problem will be achieved.

D. Fuzzy Decision Maker

In this paper, fuzzy decision maker is employed to choose the most preferred and satisfying solution [19]. The membership function is defined for each objective function set to be maximized through

\[
\mu_i^* = \begin{cases} 0, & f_i^* \leq f_i^\min \\ \frac{f_i^* - f_i^\min}{f_i^\max - f_i^\min}, & f_i^\min \leq f_i^* \leq f_i^\max \\ 1, & f_i^* \geq f_i^\max. \end{cases}
\]

The range of the objective function \(f_i\) specified from the payoff table is abbreviated as \(f_i^\min\) and \(f_i^\max\). Taking into account the individual membership function, the total
Fig. 1. Flowchart of the proposed framework for an electricity retailer.
TABLE I

<table>
<thead>
<tr>
<th>Computational Size of the Problem</th>
</tr>
</thead>
<tbody>
<tr>
<td># of binary variables</td>
</tr>
<tr>
<td># of real variables</td>
</tr>
<tr>
<td># of constraints</td>
</tr>
</tbody>
</table>

TABLE II

<table>
<thead>
<tr>
<th>Classification of Daily Load Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level</td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td>Valley (V)</td>
</tr>
<tr>
<td>Shoulder (S)</td>
</tr>
<tr>
<td>Peak (P)</td>
</tr>
</tbody>
</table>

The membership function of the \( r \)th Pareto-optimal solution, i.e., \( \mu^r \), can be stated as follows:

\[
\mu^r = \frac{\sum_{i=1}^{P} w_i \mu^r_i}{\sum_{i=1}^{P} w_i}
\]

where \( w_i \) is the weighting of the \( i \)th objective function in the MMP problem selected by the system operator based on the importance of objective functions. It is worth mentioning that the most satisfactory Pareto-optimal solution or the final solution of the MMP problem based on the adopted weighting factors is a solution possessing the maximum total membership value, i.e., \( \mu^r \).

The procedure of the full proposed framework as a flowchart is depicted in Fig. 1. Furthermore, the size of the problem is represented in Table I in terms of binary variables, real variables, and constraints.

IV. CASE STUDY

Realistic case study is adopted in this paper to implement the proposed model on the basis of the data pertaining to Iberian Peninsula electricity market available in [32] while one month is considered for the contract period, i.e., June 2010. It is assumed that a portion of this market’s demand is retailer’s demand. The proposed framework is implemented in the General Algebraic Modeling System [33], which is a high-level modeling language being utilized for mathematical programming and optimization. MIP problem is solved exploiting solver CPLEX. The system used to solve the proposed problem is a personal computer with Core2-Duo Intel Processor of 2.66-GHz clock speed and 3-GB random access memory.

A stepwise price–quota curve consisting of 100 steps is used as [4] to model the relationship between the selling price and the client demand supplied by the retailer. There are also three types of clients taken into consideration, namely, residential, commercial, and industrial, with their demand deconstructed into three load levels, which are denoted by peak, shoulder, and valley, as indicated in Table II.

The data pertaining to the price and the upper bound of the first block of the contracting curve of each contract are represented in Table III. Nine extra blocks with equal size are included in each contract with price growth of 10% considered for subsequent block. Correspondingly, the data available in Table III can be used to calculate the remaining blocks. Two hundred scenarios are generated utilizing LMCS to implement the presented stochastic framework, causing an extremely high computational burden for the problem to be solved considering all scenarios. Hence, the scenario reduction technique is applied to reduce the number of generated scenarios, wherein similar scenarios and the ones having low probability are omitted. After applying the scenario reduction, 20 scenarios have remained, leading to appreciably decreased computational burden of the presented stochastic framework.

A 17-point Pareto set is derived through solving the multiobjective problem. The most preferred Pareto solution is selected as the solution with the highest total membership value employing the proposed fuzzy decision maker. The Pareto set is depicted in Fig. 2, in which the market share of the retailer for each of its customer groups versus the profit is shown.

As shown in Fig. 2, these two objectives are conflicting, i.e., an increase in each one causes a decrease in the other one and vice versa. The maximum profit obtained by the retailer in one month is € 55 139 330, which is ideal revenue, but having the least market share. In this state, the retailer supplies 62% of residential customers, 10% of industrial customers, and 58% of commercial customers. As previously mentioned, the retailer may select the cost strategy where the market share is intended to be maximized by the retailer.
One of the most significant tools toward this purpose is to reduce the energy selling price. In spite of decreasing profit in the short term on cost strategy, if strategies are successful, increasing market share leads to increase in profit. Thus, there should be a tradeoff between the profit of the retailer and the energy selling price to different client groups. In this regard, total offered price to customers can be limited to 126.5 (€/MWh) by the retailer, leading to €1,875,230 profit while supplying 99% of residential and commercial customers and 81% of industrial customers. In other words, taking into consideration the selling price in the two-objective programming of the investigated retailer, the retailer encounters €53,264,100 decrease in profit, which is remarkable, although the retailer’s share of supplying customers’ demand increases. Moreover, it can be seen that residential customers have the highest offered price elasticity.

According to the preceding descriptions, the payoff table of the optimization problem would be as follows:

\[
\Phi = \max f_1 \left( \frac{55,139,330}{1,875,230} = 205.8 \right) \min f_2 \left( \frac{187,106,970}{1,875,230} = 126.5 \right).
\]

First, equal weighting factors are selected for two objective functions in order to choose the best solution among all Pareto solutions; the obtained results are represented in Table IV.

The total membership value of all objective functions is 0.620 in this case. The higher the membership value, the better and more ideal the solution is on decision making. If uniform weighting factors are selected, the profit would be €45,106,970, which is far from its minimum value. It is worth mentioning that the two objectives are competing, i.e., the profit is maximal, if only the selling price is kept maximal. However, the proposed multiobjective framework attempts to maximize the profit, whereas the selling price is considered to be minimized. The market share of the retailer and its optimal selling price to customers are depicted in Table V. For example, it can be observed from this table that 5800-MW energy purchased by the retailer is obtained from forward contract for this case.

Note that getting more profit is prior to achieve the largest number of customers for the retailer. Different preferred weighting factors can be assigned to the objective functions in the presented method. Table VI indicates the results (Case 2).

As a larger weighting factor is assigned to the profit, it has been improved while the sum of selling prices is raised. The nicety of profit is increased by 16%, i.e., from 81.2% to 97.2%. The optimal selling price offered to customers along with market share of the retailer is represented in Table VII. In this case, as the retailer supplies low demand at some hours, the power is sold to the pool market by the retailer.

On the other hand, it may be more significant for the retailer to have larger market share rather than the profit in order to get the larger number of customers. The results obtained through considering higher weighting factor for the selling price are given in Table VIII. The nicety of the selling price in this case is improved by 53.3%, i.e., from 42.9% to 96.2%, which is represented in Table IV. In addition, the optimal selling price offered to the customers and the market share of the retailer are provided in Table IX.

If retailer takes the strategy to gain more profit, it follows the sources with more uncertainty. Hence, the amount of its forward contracts reduces and supplies more from pool market. It can be observed from Table X that, with the increase in retailer’s profit over different cases, the amount of its forward contracts reduces.

So far, there is not any published paper determining the optimal strategy of a retailer through a multiobjective framework. Thus, the performance of the proposed method cannot be
TABLE X
AMOUNT OF FORWARD CONTRACTS

<table>
<thead>
<tr>
<th>Case</th>
<th>Forward contract (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>5,800</td>
</tr>
<tr>
<td>Case 2</td>
<td>4,200</td>
</tr>
<tr>
<td>Case 3</td>
<td>8,300</td>
</tr>
<tr>
<td>Minimum profit</td>
<td>9,000</td>
</tr>
<tr>
<td>Maximum profit</td>
<td>3,400</td>
</tr>
</tbody>
</table>

TABLE XI
PARETO-OPTIMAL SOLUTIONS OBTAINED FROM THE NBI METHOD

<table>
<thead>
<tr>
<th>Solution number</th>
<th>Membership</th>
<th>Profit</th>
<th>Selling prices</th>
<th>Overall membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.000</td>
<td>0.000</td>
<td>0.500</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.996</td>
<td>0.065</td>
<td>0.531</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.995</td>
<td>0.132</td>
<td>0.563</td>
<td></td>
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<tr>
<td>4</td>
<td>0.964</td>
<td>0.244</td>
<td>0.604</td>
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</tr>
<tr>
<td>5</td>
<td>0.909</td>
<td>0.340</td>
<td>0.625</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>0.839</td>
<td>0.424</td>
<td>0.632</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0.760</td>
<td>0.501</td>
<td>0.630</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0.674</td>
<td>0.574</td>
<td>0.624</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0.585</td>
<td>0.644</td>
<td>0.615</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.490</td>
<td>0.710</td>
<td>0.600</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>0.391</td>
<td>0.773</td>
<td>0.582</td>
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</tr>
<tr>
<td>12</td>
<td>0.344</td>
<td>0.807</td>
<td>0.575</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>0.292</td>
<td>0.837</td>
<td>0.565</td>
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</tr>
<tr>
<td>14</td>
<td>0.241</td>
<td>0.867</td>
<td>0.554</td>
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</tr>
<tr>
<td>15</td>
<td>0.191</td>
<td>0.898</td>
<td>0.544</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>0.083</td>
<td>0.955</td>
<td>0.519</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>0.000</td>
<td>1.000</td>
<td>0.500</td>
<td></td>
</tr>
</tbody>
</table>

TABLE XII
PARETO-OPTIMAL SOLUTIONS OBTAINED FROM THE ε-CONSTRAINT TECHNIQUE

<table>
<thead>
<tr>
<th>Solution number</th>
<th>Membership</th>
<th>Profit</th>
<th>Selling prices</th>
<th>Overall membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.000</td>
<td>0.000</td>
<td>0.500</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.997</td>
<td>0.063</td>
<td>0.530</td>
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</tr>
<tr>
<td>3</td>
<td>0.995</td>
<td>0.125</td>
<td>0.560</td>
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</tr>
<tr>
<td>4</td>
<td>0.981</td>
<td>0.188</td>
<td>0.584</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.962</td>
<td>0.25</td>
<td>0.606</td>
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<td>0.620</td>
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<tr>
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<td>0.825</td>
<td>0.438</td>
<td>0.631</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0.760</td>
<td>0.500</td>
<td>0.630</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.681</td>
<td>0.563</td>
<td>0.622</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>0.609</td>
<td>0.625</td>
<td>0.617</td>
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</tr>
<tr>
<td>12</td>
<td>0.526</td>
<td>0.688</td>
<td>0.607</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>0.430</td>
<td>0.750</td>
<td>0.590</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>0.334</td>
<td>0.812</td>
<td>0.573</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>0.231</td>
<td>0.875</td>
<td>0.553</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>0.114</td>
<td>0.937</td>
<td>0.526</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>0.000</td>
<td>1.000</td>
<td>0.500</td>
<td></td>
</tr>
</tbody>
</table>

V. Conclusion

An efficient tool has been proposed in this paper for the retailer to derive optimal selling price to customers and to manage a portfolio pertaining to the forward contract in the stochastic multiobjective MIP framework implemented in the medium-term period. In addition, random scenario generation procedure is implemented employing roulette wheel mechanism and LMCS. In the proposed framework, competing objective functions of the retailer comprising profit and selling price are optimized as a multiobjective problem. In addition, Pareto set is generated via NBI method, and Benders decomposition has been applied as a robust algorithm to achieve the optimal solution. According to the simulation results and discussions given, it can be implied that the proposed stochastic multiobjective framework has two main benefits: First, the two conflicting objectives of the problem, i.e., maximization of the profit and minimization of the selling price, are compromised through presenting a flexible framework. Second, forward contract portfolio and the optimal selling prices are more efficiently utilized.

REFERENCES


