A Decision-Support System Based on Particle Swarm Optimization for Multiperiod Hedging in Electricity Markets

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Abstract

This paper proposes a particle swarm optimization (PSO) approach to support electricity producers for multiperiod optimal contract allocation. The producer risk preference is stated by a utility function (U) expressing the tradeoff between the ex- pectation and variance of the return. Variance estimation and ex- pected return are based on a forecasted scenario interval deter- mined by a price range forecasting model developed by the au- thors. A certain confidence level is associated to each forecasted scenario interval. The proposed model makes use of contracts with physical (spot and forward) and financial (options) settlement. PSO performance was evaluated by comparing it with a genetic algo- rithm-based approach. This model can be used by producers in deregulated electricity markets but can easily be adapted to load serving entities and retailers. Moreover, it can easily be adapted to the use of other type of contracts.

Index Terms: Contracts, electricity markets, genetic algo- rithms, hedging, particle swarm optimization, risk management.

I. INTRODUCTION

TRADITIONALLY, electricity market models were based on monolithic regulated public utilities, where the prices were stable and predictable over a relatively long-term horizon, and therefore, the risk involved on the energy business was low.

Similarly to other sectors, electricity markets have undergone a re-regulation and liberalization process, attempting to create more desirable markets. However, electricity market is a special case of a commodity market, due to the difficulty on storing electric energy and to the necessity of maintaining the system constantly in balance.

All over the world, the electric sector liberalization and restructuration process has as core a spot market managed by a market operator (MO), where the generators and the load serving entities sell or buy, respectively, the energy on an hour or half-hour basis.

The electric energy non-storability causes very wide fluctuations on spot prices that, when associated to heat or cold waves, can lead the spot price to climb up to 1000% for short periods of time [1]. This is unusually high even when compared with other commodities markets. Another implication of the electricity non-storability is the impossibility of transferring a certain amount of energy from one part of the world to another or even from a neighboring region without considering the electric transmission constraints.

Moreover, charge characteristics (like seasonality, mean-reversion, and stochastic growth) and producers characteristics (generation technology, generators availability, fuel prices [2] and technical restrictions) introduce big challenges but also high risks, such as high price volatility.

The liberalization of the electric sector leads to fierce competition on several activity sectors and, in particular, on the production sector [3], [4]. Power producers have to change the way they do business, evolving from monopolist market to unbundled companies in direct competition. They also have to adapt themselves to a new reality, which may require reducing the overcapacity by closing power plants, abandoning plans for constructing new ones, and considering plant efficiency as an increasingly important factor. This requires to rethink the entire productive process and to study the possibility of constructing new lower capacity power plants using new technologies.

Before the restructuration and liberalization process, prices were stable and predictable over a relatively long-term horizon, and therefore, the risk involved on the energy business was low. Electricity market participants, namely, producers, now more than ever need tools that allow them to practice the hedge against the volatility of the spot price.

Responding to that need, derivatives markets allow negotiating contracts with underlying asset the electric energy. These markets have an important role on practicing the hedge against the volatility of the spot market price and simultaneously to eliminate the risk of credit and to turn the market more liquid. Derivatives markets negotiate forward, futures, and options contracts. Forward and futures contracts are similar, having as the main difference the fact that futures contracts are exclusively of financial type while forward contracts comprise the physical delivery of the energy. Note that, for instance, in Nord Pool, forward and futures contracts are exclusively of financial type, having as the main difference the duration. Futures are short-term contracts and forward are long-term contracts. The financial settlement for forward contracts involves no daily mark-to-market settlement and therefore requires posting cash only during the delivery period, starting at the contract's due date. Options contracts main difference from forward and futures contracts is the fact that they give to the buyer the exercising decision right, but to have this right, he has to previously pay a certain amount of money designated by premium.

High price volatility associated to contracts with complex characteristics is a hard task and has been a topic of some studies reported in the literature. In these studies, some models have been proposed; in [5], solutions for electricity producers in the field of financial risk management for electric energy contract evaluation using efficient frontier as a tool to identify the preferred contract portfolio are proposed. A decision support system based on stochastic simulation, optimization, and multicriteria analysis is applied to the electricity retailer in [6]. A statistical study of direct and cross hedging strategies using futures contracts in an electricity market is presented in [7] and [8]. A framework to obtain the optimal bidding strategy of a thermal price-taker producer on a pool-based electric energy market is presented in [9]. None of the cited studies make use of option pricing analysis or other decision analysis techniques used in modern finance to evaluate uncertainties. The use of option pricing analysis [10] or other decision analysis techniques instead of portfolio models is based on the assumption that the market is complete. However, uncertainties associated to generator availability, fuel prices, technical restrictions, and weather conditions turn difficult, if not impossible, to find a replicating portfolio that perfectly matches the future spot market payoffs. The market power exercised by some agents is also a source of uncertainty. In addition, several markets around the world are still on their child stage, with a small number of financial tools for an efficient risk management. Another issue in power markets is that electricity cannot be stored for later use. As a consequence, the strategy of buying the asset today to offset part of future losses does not apply. The closest strategy is to buy forward or futures contracts. On complete market and to avoid arbitrage opportunities, the delivery price of forward and futures contracts should be equal to the expected spot market price for the delivery period, which does not always happen. Based on this, we conclude that electricity markets are not complete, and so, risk attitudes and mean variance frontiers are still relevant.

In this paper, an approach to find the optimal contracts portfolio for electricity producers is proposed. Contrary to most techniques found in the literature, the approach presented has as an advantage the possibility of being applied to multiperiod programming. Due to the complexity of the problem, we make use of *particle swarm optimization* (PSO) [11] to find the optimal solution. The producer risk preference is stated by the maximization of a mean variance utility function (U) in terms of the tradeoff between the expectation and variance of the return. A mean variance formulation was chosen to the value at risk (VAR) criterion, because the value at risk formulation generally provides a hard constraint to optimization problems [12]. However, as demonstrated in [13], the use of a Lagrangean relaxation on the value at risk formulation results in a formulation that resembles the mean variance very closely.

Finding an optimal portfolio based on a predicted single value is not a good practice in risk management, unless we are 100% certain that the price predicted is correct. Due to the specific nature of the underlying asset, price forecast on electricity markets has been a hard task. Factors like charge characteristics (seasonality, mean-reversion, and stochastic growth) and producer's characteristics (technology, generation availability, fuel prices, technical restrictions, and import/export) are at the origin of the high price volatility in electricity markets.

Due to the characteristics of mean variance formulation, we developed a method [14], [15] based on historical data that allows to forecast a maximum and a minimum value for each period of the system marginal price (SMP), with a certain confidence level α which is useful to calculate the mean and variance of the total return.

PSO and genetic algorithm (GA) performance are evaluated to show that PSO is a very successful meta-heuristic technique for this particular problem.

This paper is organized as follows. In Section II, a short overview of PSO is made. Section III provides the problem formulation description. In Section IV, a case study is presented, and Section V presents some relevant conclusions.

II. Particle Swarm Optimization

PSO [11], [16] is an evolutionary computational algorithm inspired by a natural system. On a given iteration, a set of solutions called "particles" move around the search space from one iteration to another according to rules that depend on three factors: inertia (the particles tend to move in the direction they have previously moved), memory (the particles tend to move in the direction of the best solution found so far in their trajectory), and cooperation (the particles tend to move in the direction of the global best solution).

The movement rule of each particle can be expressed by

$$X_i^{\text{new}} = X_i + V_i^{\text{new}} \tag{1}$$

where

X_i^{new}	new position of the particle i
X_i	current position of the particle i
V_i^{new}	new velocity of the particle i and is given by

$$\begin{aligned} V_i^{\text{new}} = \operatorname{dec}(t) \cdot V_i + \operatorname{rand}_{i,k} \cdot \alpha_{i,k} \cdot (\text{pbest}_i - X_i) \\ + \operatorname{rand}_{i,j} \cdot \alpha_{i,j} \cdot [\text{pbest}(\text{gbest}) - X_i] \end{aligned} \tag{2}$$

where,

dec(t)	inertia weight that decreases with the number of iterations;
V_i	previous velocity of the particle i
$\operatorname{rand}_{i,k}$ $\operatorname{rand}_{i,j}$	random weights acceleration, from a uniform distribution in [0, 1], for each time step;
$\alpha_{i,k}$	weight fixed at the beginning of the process designated by cognitive acceleration parameter;
$\alpha_{i,j}$	weight fixed at the beginning of the process designated by social acceleration parameter;
pbest_i	particle i best position found so far;
pbest(gbest)	best global position of all particles found so far.

The inertia term controls the exploration and exploitation of the search space. If the velocity is too high, then the particles could move beyond a global solution. On the contrary, if velocity is too low, the particles could be trapped into a local optimum. To achieve faster convergence and avoiding the problems described above, we make the inertia term vary with the number of iterations and limit the maximum velocity of particles to $\mathrm{V}_{\max}$.

III. Problem Formulation

To make a good resource management, producers constantly have to make short- and long-term decisions. Finding the optimal portfolio for an electricity producer is a hard task, due to high price volatility and to the specific characteristics of the contracts that he can establish. Some of the contracts have nonlinear characteristics, which makes the decision even more difficult. Facing this new reality, producers need decision-support systems to help them to decide which type of contracts they shall establish for the period or periods in question.

So, a multiperiod decision-support system is proposed, which aims to find the “unknown optimal” portfolio that maximizes the expected return and, simultaneously, allows the practice of the hedge against the SMP volatility. To achieve this, the decision-support system maximizes a mean variance utility function (U) of the total return (π). Costs of sales (like taxes, market commissions, and others) were not considered.

Contractual diversification is the key issue for an efficient risk management. To achieve this, it is assumed that producers can make use of contracts with physical settlement (spot and forward contracts) and contracts with financial settlement (options contracts).

A. *Spot Contracts*

The spot market becomes the core of the main deregulated electricity markets around the world. Producers make extensive use of this market to sell their energy on an hour or half-hour basis. The revenue from the short position (who sells has a short position and who buys has a long position) obtained by the producer is dependent of the period i and scenario j and is given by

$$r_{i,j}^{\mathrm{ss}} = \mathrm{SMP}_{i,j} \times e_i^{\mathrm{ss}} \tag{3}$$

where

- $r_{i,j}^{\mathrm{ss}}$ revenue, in Euro, of the short position obtained by the producer in the spot market, for period i and scenario j;
- $\mathrm{SMP}_{i,j}$ System Marginal Price, in Euro/MWh, for period i and scenario j;
- e_i^{ss} energy amount, in MWh, that the producer decides to sell in the spot market for period i.

B. *Forward Contracts*

One of the most common methods used to hedge against spot price volatility is to establish forward contracts. Forward contracts are bilateral agreements in which two parts agree mutually on the characteristics (quantity, price, point of delivery, and date/time). The payment is made only on a future date, eliminating the risk associated to price variation. Most forward contracts are traded in organized and over-the-counter (OTC) markets.

As stated previously, producers can make use of forward contracts to sell energy. So, the revenue from short forward positions obtained by the producer is given by (4). In our method, the delivery period in forward contracts is the same of all period in analysis

$$r^{\mathrm{sf}} = k^{\mathrm{sf}} \times e^{\mathrm{sf}} \tag{4}$$

where

- r^{sf} revenue, in Euro, of the short position obtained by the producer in forward contracts;
- k^{sf} delivery price, in Euro/MWh, of the forward contract;
- e^{sf} energy amount, in MWh, that the producer decides to sell in forward contracts.

Because on forward contracts the delivery price is fixed, its revenue is only dependent on the delivery price and quantity established in the contract.

In this study, producers are not allowed to take any advantage of arbitrage opportunities, so not to obtain *long forward* positions.

C. *Options Contracts*

Traditionally, options in electricity markets are of financial type. There are four positions types on options contracts, and they are: *short call, long call, short put*, and *long put*. However, in the decision-support system, it is assumed that producers could only establish *short call* and *long put* positions. These positions are similar to the positions that the producer can establish to sell the produced energy with physical settlement. If the producer is allowed to establish the four positions types, the quantities to practice the hedge would be almost infinite if a financial limit is not established. In some electricity markets, options are on futures with daily settlement. The settlement price could be equal to the simple average of all 24 h for base load futures contracts or equal to the simple average of the prices for the hours between 8:00 A.M. and 20:00 P.M. for peak load futures contracts. It is also assumed that they are European-style options. (European-style options can only be exercised at the beginning of the delivery date, while American-style options can be exercised at any time until the delivery date.)

The characteristics of electricity prices, such as mean reversion, high degree of skewness, and non-constant volatility, exclude its modeling using commodity cost-of-carry models; thus, Black & Sholes formula is not applicable to electricity option pricing. A procedure to evaluate the price of options in electricity markets, known as *risk-neutral valuation*, is presented in [17]. Binomial model could also be applied to evaluate electricity options price, but it requires some adjustments.

For the short call position, the buyer only exercises the option if the SMP is greater than the exercise price. In our method, the delivery period in call options is the same as all periods in analysis.

The payoff for the short call position is given by

$$\text{Payoff}^{\text{sc}}_{i,j} = e^{\text{sc}} \times [\min(k^{\text{sc}} - \text{SMP}_{i,j}, 0) + p^{\text{sc}}] \quad (5)$$

where

$\text{Payoff}^{\text{sc}}_{i,j}$	payoff, in Euro, of the short call position, for the period i and scenario j;
p^{sc}	premium, in Euro/MWh, of the call option;
k^{sc}	delivery price, in Euro/MWh, of the call option;
$\text{SMP}_{i,j}$	System Marginal Price, in Euro/MWh, for the period i and scenario j;
e^{sc}	energy, in MWh, associated to the short call position obtained by the producer.

Because the call option exercise is dependent on the system marginal price scenario, the short call position payoff is dependent on the scenario j considered for each period i

For the long put position, the option buyer (producer) will exercise it if the SMP is lower than the exercise price.

The payoff for the long put position is given by

$$\text{Payoff}^{\text{lp}}_{i,j} = e^{\text{lp}} \times [\max(k^{\text{lp}} - \text{SMP}_{i,j}, 0) - p^{\text{lp}}] \quad (6)$$

where

$\text{Payoff}^{\text{lp}}_{i,j}$	payoff, in Euro, of the long put position, for period i and scenario j;
p^{lp}	premium, in Euro/MWh, of the put option;
k^{lp}	delivery price, in Euro/MWh, of the put option;
$\text{SMP}_{i,j}$	System Marginal Price, in Euro/MWh, for period i and scenario j;
e^{lp}	energy, in MWh, associated to the long put position obtained by the producer.

Similarly to call options, the put option exercise is dependent on the SMP scenario; being so, the payoff is dependent on the considered scenario j for the period i. It is assumed that the delivery period on put options contracts is the same for all periods in analysis.

D. Optimization Problem

Several techniques have been developed for price forecast, using, for example, time series models [18] or artificial neural networks [19]. However, most of them try to forecast a single price for the period in question. Making decisions based only on a single forecasted value is risky. This is due to the fact that the values obtained by these techniques have always an error margin that depends on several factors such as: number and type of variables used in price forecast and of random factors that could influence the SMP.

Trying to overcome this problem, a method was developed [14], [15] based on historical data that allows finding a maximum and a minimum value for the SMP for the period in question. A certain confidence level α is associated to the forecasted interval.

The optimization problem aims to maximize a mean variance utility function of the producer total return for the period in question. The mathematical formulation is given by

$$\text{Maximize } U(\pi^{\text{total}}) = E(\pi^{\text{total}}) - \lambda \times \text{Var}(\pi^{\text{total}}) \quad (7)$$

subject to:

$$e_{\min} \le e_i^{\text{ss}} + e^{\text{sf}} \le e_{\max} \quad (8)$$

$$e_i^{\text{ss}}, e^{\text{sf}}, e^{\text{sc}}, e^{\text{lp}} \ge 0 \quad (9)$$

where

$$E(\pi^{\text{total}}) = \text{Mean}(\pi^{\text{máx}}, \pi^{\min}) \quad (10)$$

and,

$$\text{Var}(\pi^{\text{total}}) = \sum_{i=1}^{2}\sum_{j=1}^{2} \text{cov}_{i,j}(\pi^{\max}, \pi^{\min}) \quad (11)$$

with

$$\pi^{\max} = [\pi_1^{\max}, \ldots, \pi_T^{\max}] \quad (12)$$

and,

$$\pi^{\min} = [\pi_1^{\min}, \ldots, \pi_T^{\min}]. \quad (13)$$

The variables meaning from (7) to (13) is as follows:

π^{total}	producer total return in Euro;
$E(\pi^{\text{total}})$	expected value of the return for the maximum and minimum price range forecast for all periods i in Euro;
$\text{Var}(\pi^{\text{total}})$	variance of the return for the maximum and minimum price forecast for all periods i, in Euro;
$\text{cov}_{i,j}(\pi^{\text{máx}}, \pi^{\min})$	covariance matrix element (i,j) of the returns for the maximum and minimum price range forecast, in Euro;
$\pi_i^{\max}$	return for the period i based on the maximum price forecast for that period, in Euro;
$\pi_i^{\min}$	return for the period i based on the minimum price forecast for that period, in Euro;
T	number of the considered periods;
λ	producer risk aversion factor;
$e_{\min}$	minimum energy, in MWh, that the producer can produce;
$e_{\max}$	maximum energy, in MWh, that the producer can produce;
e_i^{ss}	energy amount, in MWh, that the producer decides to sell on the spot market for period i;
e^{sf}	energy amount, in MWh, that the producer decides to sell in forward contracts;

e^{sc} energy, in MWh, associated to the short call position obtained by the producer;

e^{lp} energy, in MWh, associated to the long put position obtained by the producer.

The mean variance formulation is comparable to the VAR formulation due to factor λ[13]. However, the mean variance formulation was used instead of a value at risk because it is computationally more efficient for a given λ and simultaneously allows practicing the hedge against the SMP volatility while the expected return is increased. The risk aversion factor λ was assumed to be equal for all periods. The value at risk formulation generally provides a hard constraint to optimization problems. Higher order information about the joint probability distribution of the payoff is necessary. In addition, the value at risk formulation is highly sensitive to the high impact of low probability events, which create "fat tails" in the distribution of payoffs.

The authors' previous work [14], [15], an interval for the SMP is determined with a certain confidence level α, revealed to be useful for the mean variance formulation because it requires not only the expected value of the total return but also its variance.

In the optimization formulation, the constraint (8) represents the operation limits. Constraint (9) guarantees that all energy quantities are positive or equal to zero.

The return π for each period i, expressed in Euro, is a function of the considered maximum or minimum price forecast scenario j for that period and is equal to the sum of all revenues and options payoffs minus the costs of production. The mathematical formulation of the return is given by

$$\pi_{i,j} = r_{i,j}^{ss} + r^{sf} - C_{i,j} + \text{Payoff}_{i,j}^{sc} + \text{Payoff}_{i,j}^{lp} \quad (14)$$

where

$$C_{i,j} = C\left(e_i^{ss} + e^{sf}\right). \quad (15)$$

Because the authors consider that options are exclusively of financial type, that is, their settlement is financial, the costs of production are only a function of the energy that the producer foresees to sell in the spot market and the energy established on forward contracts. The costs of production for each period i and scenario j is given by (15).

E. Penalty Functions

To satisfy constraints (8) and (9) for each period, we use penalty functions that are added to (7). The penalty function used to satisfy (8) is given by

$$p_{f1} = \begin{cases} 0, & \text{if } e \geq e_{\min} \text{ and } e \leq e_{\max} \\ e^{100 \times a^2} - 1, & \text{otherwise} \end{cases} \quad (16)$$

where

$$a = \min[|e - e_{\min}|, |e - e_{\max}|] \quad (17)$$

and

$$e = e_i^{ss} + e^{sf}. \quad (18)$$

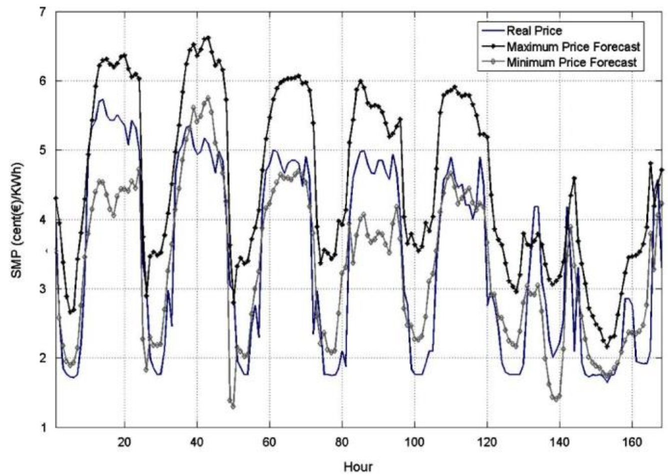

Fig. 1. Real price and price range forecast, with confidence level = = a2%, for August 18–24, 2003.

To satisfy constraint (9), a penalty function given by (19) and (20) is used as follows:

$$p_{f2} = \begin{cases} 0, & \text{if } e_i^{ss,sf,sc,lp} \geq 0 \\ e^{100 \times b^2} - 1, & \text{otherwise} \end{cases} \quad (19)$$

where

$$b = \left| e_i^{ss,sf,sc,lp} \right|. \quad (20)$$

IV. Case Study

This section presents an example of a producer that wants (in July 2003) to find the optimal contracts portfolio for the months of August to December of the same year.

Developed through the short-term method presented in [14] to increase the accuracy, the method presented in [15] is used in this example to forecast the price range between that period (August to December). Real load and price data from mainland Spanish market were used as historical data. Due to the impossi- bility to get temperature data to forecast the load for that period, real load data were used. However, in reality, the method pre- sented in [15] does not use the real load data but a "fictitious" maximum and minimum load for that period. We get "fictitious" maximum and minimum load applying scale factors that we get from the used historical data to train the neural networks. Thus, real load data from the previous year could also be used with good results. The forecasted method developed by the authors, and presented in [15], makes use of artificial neural networks and clustering techniques.

For example, the price range forecast and the real price for August 18–24, 2003 is presented in Fig. 1. The real load for the same week is presented in Fig. 2.

PSO was used to find the best solution. A comparison be- tween the PSO and GA algorithm is provided.

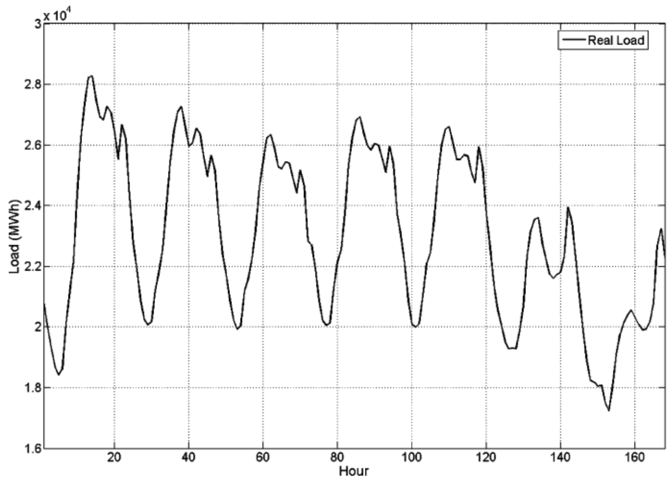

Fig. 2. Real load for August 18–24, 2003.

TABLE I
OPTIONS CONTRACTS CHARACTERISTICS

	Exercise Price (Euro/MWh)	Premium (Euro/MWh)
Short Call	30.10	2.63
Long Put	32.32	5.09

A. Contracts Characteristics

Options contracts characteristics with delivery period from August to December are presented in Table I.

For the forward contracts with delivery period from August to December, a price was assumed to be equal to 25 Euro/MWh.

The production cost function considered is represented by

$$C(P_g) = 100 + 0.3 \times P_g + 0.02 \times P_g^2 \tag{21}$$

with $\mathrm{P}_g$in MW, C in Euro/h, $P_g^{\max} = 200$ MW, and $=$ 5 $P_g^{\min}$ MW.

The producer's cost function is considered the same for the entire period in analysis (five months).

The main issue in mean variance formulation is the right choice of the producer risk aversion factor λbecause the results are directly dependent of that factor. So, in this particular study case, we use a risk aversion factor λequal to 1. Normally the risk aversion factor λvaries between zero and three. We admit a risk aversion factor λconstant for the entire period; however, due to the dependence of the results with the risk aversion factor λ, a study of that relationship will also be made.

B. PSO Parameters

The PSO parameters used to find the best solution are presented in Table II.

C. GA Parameters

The GA parameters used to find the best solution are presented in Table III.

TABLE II
PSO PARAMETERS

Parameter	
Nº. of Particles	20
Nº. of Iterations	20000
Nº. of Evaluations	400000
Cognitive Acceleration	2
Social Acceleration	2
Initial inertia weight	0.9
Final inertia weight	0.4
Maximum velocity (V_{max})	10

TABLE III
GA PARAMETERS

Parameter	
Population Size	20
Nº. of Generations	20000
Nº. of Evaluations	400000
Crossover Rate	0.8
Mutation Rate	0.2

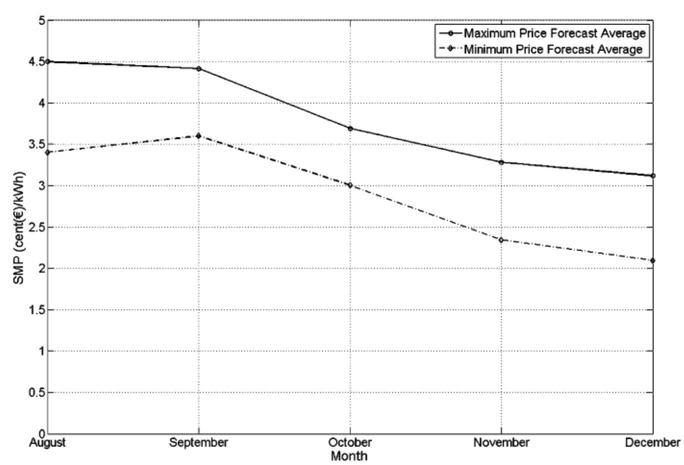

Fig. 3. Monthly average of the SMP range forecast.

D. Results

In this section, results are presented, and an evaluation of PSO performance is made and compared with a GA. The stopping criterion was the maximum number of evaluations (fixed in 400 000 evaluations). With 20 particles in the PSO and a population size of 50 for the GA, 20 000 iterations for PSO and 8000 generations for GA were performed. Due to random initialization, the trajectory for each run is different; so, we used ten runs to calculate the average and the standard deviation of the results.

To find the optimal energy quantities to establish in forward and options contracts, the hedging period is divided in subperiods with duration of one month. This allows reducing the number of variables and consequently turns the optimization problem lighter.

The graphical representation of the monthly average of the SMP range forecast is presented in Fig. 3.

TABLE IV
PSO RESULTS FOR THE NEXT FIVE MONTHS

Positions	Average Quantity (MWh)	Standard Deviation (MWh)
Short Spot	138270	9417
Short Forward	596980	9382
Short Call	160350	15050
Long Put	71732	862

TABLE V
GA RESULTS FOR THE NEXT FIVE MONTHS

Positions	Average Quantity (MWh)	Standard Deviation (MWh)
Short Spot	101470	13902
Short Forward	630200	10841
Short Call	93639	19357
Long Put	85550	3203

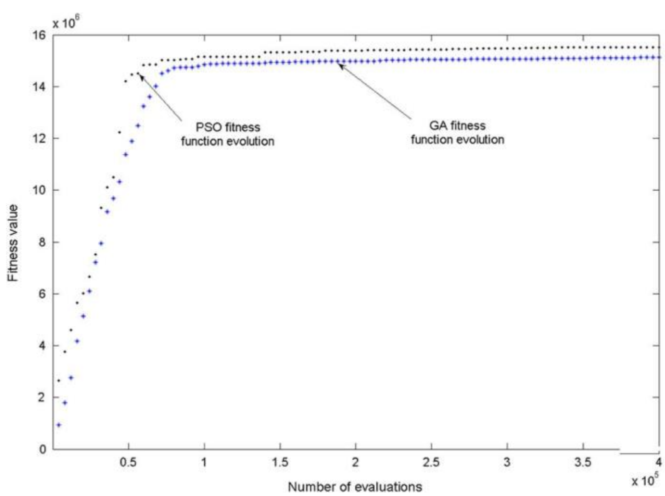

Fig. 4. PSO and GA fitness function evolution.

Based on this information, we find the energy that the producer should sell in spot, forward, and options contracts for the next five months.

The results for the considered case study using PSO are presented in Table IV.

Results for the case study using a GA are presented in Table V.

Comparing the standard deviation for each solution (see Tables IV and V), we conclude that PSO is more robust than the GA.

The fitness function evolution for PSO and GA are presented in Fig. 4. From Fig. 4, we conclude that PSO, when compared with GA, finds a better solution using a smaller number of iterations.

The mean and the standard deviation of the fitness functions for the ten runs are presented in Table VI. Table VI also includes

TABLE VI
PSO AND GA FITNESS FUNCTION COMPARISON

Algorithm	Mean Fitness Value	Std. Fitness Value	Mean Time (sec.)
PSO	15451500	47376	103.3
GA	15220000	96167	968.1

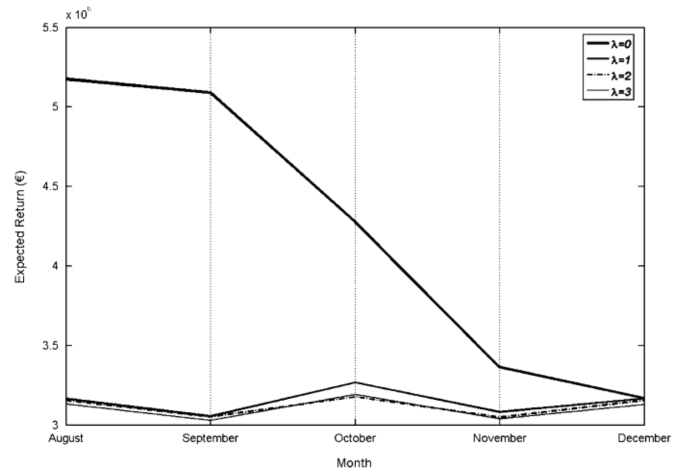

Fig. 5. Producer expected return in function of risk aversion factor γ.

the mean time necessary to reach the optimal solution for PSO and GA.

It can be verified from Table VI that, for this particular problem, PSO is faster than GA (mean time), finds better solutions (mean fitness value), and is more robust (standard deviation). These simulations were made on an ASUS L5GX laptop, with a P4 3.2-GHz processor and 1 GB of memory.

E. Expected Return and Associated Risk

The mean variance formulation allows maximizing the expected return while limiting the risk. However, the optimal quantities that the producer shall sell for each period are directly dependent of the risk aversion factor λ. In Fig. 5, the expected return for each month as function of the risk aversion factor λ is presented. These values were obtained using the PSO meta-heuristic and the parameter values shown in Table II. Besides the optimum PSO parameters being also dependent on the fitness function, experimentations show that the number of evaluations used does not compromise the results and allows achieving the optimal solution.

The risk as a function of factor risk aversion factor $\lambda$is presented in Fig. 6.

The spot energy quantities the producer shall sell on the spot market for each period as a function of risk aversion factor $\lambda$are presented in Fig. 7.

Analyzing Figs. 5 and 6, we conclude that for the same risk aversion factor λ, the bigger the expected return, the bigger the risk (standard deviation of the return) to which the producer is exposed. Also from the same figures, the maximum expected return as well as the maximum risk (standard deviation of the

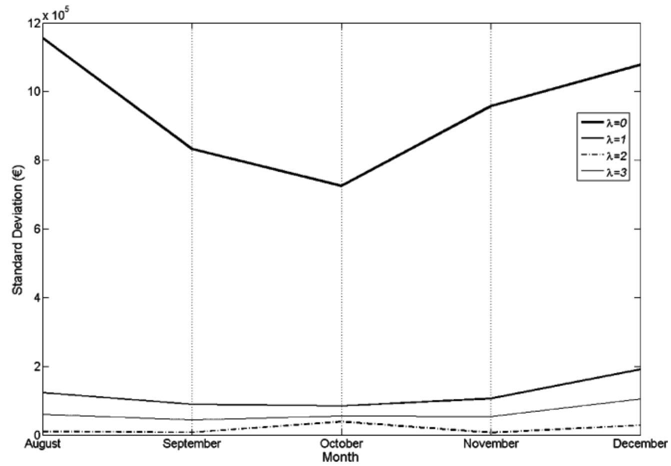

Fig. 6. Risk in function of risk aversion factor γ.

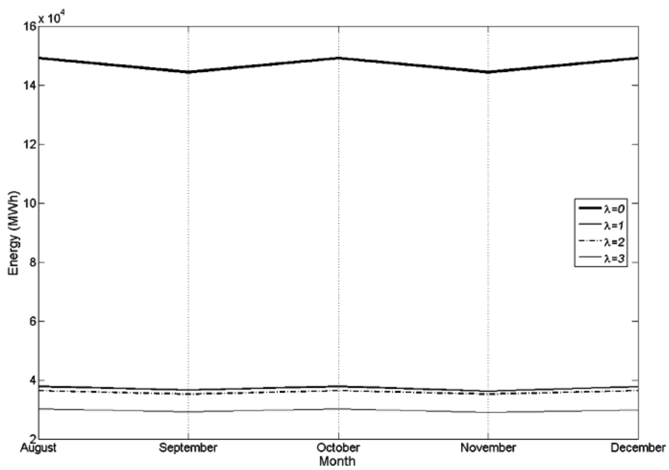

Fig. 7. Optimal energy quantities that producer should sell in spot market in function of risk aversion factor γ.

return) are reached with a risk aversion factor λ equal to zero. The reason for this is that when risk aversion factor is zero, the producer is indifferent to risk, and therefore, he will sell more energy on the spot market, as it can be seen in Fig. 7. In fact, as expected, the risk (standard deviation of the return) is inversely proportional to the risk aversion factor λ, and so is the energy that the producer will sell in the spot market.

F. Energy to Sell on Spot Market

After defining the optimal quantities to establish in forward and options contracts, the producer has to decide every day the amount of energy that he shall sell in the spot market for the next day.

In this system, it is assumed that the energy established in forward contracts is delivered on equal quantities on each hour during the entire five months. This is equal to the total energy divided by the number of hours of the five months. It was also assumed that options contracts have hourly settlement.

So, the quantity of energy that the producer has to delivery, due to forward contract, for each hour and $\lambda = 0$ and using the PSO results, is given by $596\,980\ \mathrm{MWh}/3672\ \mathrm{h} \times 1\ \mathrm{h} = 162.58$ MWh. The hourly settlement energy for call and put options contracts, also using PSO results, are, respectively, $160\,350\ \mathrm{MWh}/3672\ \mathrm{h} \times 1\ \mathrm{h} = 43.67$ MWh and $71\,732\ \mathrm{MWh}/3672\ \mathrm{h} \times 1\ \mathrm{h} = 19.53$ MWh.

TABLE VII
OPTIMAL QUANTITIES TO SELL IN THE SPOT MARKET FOR AUGUST 18, 2003

Position by hour		Average Quantity (MWh)	Std. Dev. (MWh)	Exp. Return (Euro)	Std. Dev. Return (Euro)
Short Spot	1	37.6479	0	4196.3	32.3
	2	37.6594	0	4205.9	15.0
	3	37.6569	0	4186.8	59.9
	4	37.6520	0	4188.3	119.7
	5	37.6478	0	4.1622	97.1
	6	37.6479	0	4169.0	97.3
	7	37.6581	0	4182.0	62.4
	8	37.6543	0	4226.1	32.0
	9	37.6497	0	4199.3	35.4
	10	37.6559	0	4169.9	48.3
	11	37.6582	0	4144.6	54.5
	12	37.6615	0	4122.4	64.6
	13	37.6633	0	4109.0	71.1
	14	37.6642	0	4107.2	74.8
	15	37.6662	0	4112.1	83.0
	16	37.6675	0	4120.7	88.8
	17	37.6679	0	4124.6	90.9
	18	37.6658	0	4114.6	81.3
	19	37.6658	0	4108.7	81.1
	20	37.6659	0	4108.0	81.7
	21	37.6643	0	4114.6	74.9
	22	37.6613	0	4113.7	63.9
	23	37.6630	0	4115.5	70.0
	24	37.6586	0	4109.2	55.7

Using the same methodology used earlier to get the optimum quantities to establish in forward and options contracts, the optimal quantities to sell in the spot market for each hour are obtained.

The optimal quantities that the producer should sell in the spot market for August 18, 2003, using PSO meta-heuristic, are presented in Table VII.

The PSO settings are: 400 000 evaluations as stopping criteria, 20 particles, and 20 000 iterations. Due to random initialization, the trajectory for each run is different; so, ten runs were performed to calculate the average and the standard deviation of the results.

V. CONCLUSION

With the liberalization and restructuration of the electricity markets, producers are more exposed to price uncertainty, making the management of their resources more difficult. Besides the uncertainty associated to the SMP, the electricity markets agents, and producers in particular, have now contractual forms that existed only on traditional commodities markets. Decision-support systems that support electricity markets agents and producers in particular reveal to be of high importance and actuality.

In this paper, a new decision-support system was proposed that allows producers to maximize their expected return while practicing the hedge against spot price uncertainty. This decision-support system has as main advantage its adaptability. Namely, it can be easily adapted to other electricity market agents, like, for example, load serving entities and brokers, and to other periods being only necessary to have the price forecast for that period.

The PSO algorithm has been used to optimize producers' return and has proven to have significant advantages in terms of robustness and computation time, when compared with a GA.

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