A Long-term Swarm Intelligence Hedging Tool Applied to Electricity Markets

Filipe Azevedo[1], Zita A. Vale[1]

Abstract. This paper proposes a swarm intelligence long-term hedging tool to support electricity producers in competitive electricity markets. This tool investigates the long-term hedging opportunities available to electric power producers through the use of contracts with physical (spot and forward) and financial (options) settlement. To find the optimal portfolio the producer risk preference is stated by a utility function (U) expressing the trade-off between the expectation and the variance of the return. Variance estimation and the expected return are based on a forecasted scenario interval determined by a long-term price range forecast model, developed by the authors, whose explanation is outside the scope of this paper. The proposed tool makes use of Particle Swarm Optimization (PSO) and its performance has been evaluated by comparing it with a Genetic Algorithm (GA) based approach. To validate the risk management tool a case study, using real price historical data for mainland Spanish market, is presented to demonstrate the effectiveness of the proposed methodology.

1 INTRODUCTION

Long-term contractual decisions are the basis of an efficient risk management. On a vertical integrated electricity market, price variations were often minimal and heavily controlled by regulators. In this structure, electricity price evolution is directly dependent on the government's social and industrial policy, and price forecasting was mainly focused on the underlying costs (namely, fuel prices and technological innovation). Any price forecasting made on that basis was tended to be over the long-term. With electricity markets re-regulation and liberalization process, this changed dramatically. Ownership on this activity sector become private rather than public or a mixture of both and competitive markets, like pools or power exchanges, has been introduced for wholesale trading.

Due to the specific nature of the underlying asset, price forecast on liberalized 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. Trying to overcome this issue, several techniques have been used for short-term price forecast in electricity markets. In [1], artificial intelligent tools are applied to forecast spot prices, namely, a combination of neural networks and fuzzy logic are used to predict prices. In fact, besides the early scepticism, neural networks have now an extensive use in load [2] and in price [3, 4, 5] forecast. Fuzzy techniques together with neural networks are used to predict possible prices range [6, 7]. Stochastic processes are also used to analyze time series. In [8], ARIMA processes, a class of stochastic processes, were used to predict next-day electricity prices in mainland Spanish and in California markets. In [9], two forecasting tools based on dynamic regression and transfer function models are presented.

However, for the agents who want to maximize their profits and simultaneously to practice the hedge against the market price volatility, the use of forward, futures and options contracts become a constant in developed electricity markets. Those types of contracts have a maturity that goes from one year to several years in the future, turning more difficult the decision process related to contracts establishment if they aren't supported with a robust price forecast methodology.

Due to long delivery periods of the contracts described above, makes more sense to forecast the market price mean value for each month and continuously review the agent position (say once a month) or each time the agent needs to consider his contractual positions already locked, than forecast the market price for periods on an hour or half-hour basis for so long periods. It is difficult to find in the literature scientific documents that deal with this problem, which is a very important subject in electricity markets risk management with high market price volatility. However, it is not a good practice in risk management to take contractual decisions based exclusively on a single forecasted value. In [10] is presented a different approach for long-term price forecast. Making use of regression models, [10] has as main goal to find a maximum and a minimum monthly Market Clearing Price (MCP) average for a programming period, with a desired confidence level α. This methodology makes use of statistical information extracted from historical data. Due to the problem complexity, the parameters are obtained using the meta-heuristic Particle Swarm Optimization (PSO) [11, 12].

Finding an optimal portfolio for a market agent and in particular for the producers, which allow hedging against market price volatility and simultaneously increase their profits, is difficult due to the complexity of the optimization problem. The scientific literature reports some studies about this matter. In [13], 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 multi-criteria analysis is applied to electricity retailer in [14]. A statistical study of direct and cross hedging strategies using futures contracts in an electricity market is presented in [15, 16]. A framework to obtain the optimal bidding strategy of a thermal price-taker producer on a pool-based electric energy market is presented in [17].

[1] GECAD – Knowledge Engineering and Decision-Support Research Group of the Institute of Engineering – Polytechnic of Porto (ISEP/IPP), Rua Dr. António Bernardino de Almeida, 4200-072 Porto, Portugal. Email: {fta, zav}@isep.ipp.pt.

This long-term risk management tool makes use of a long-term price range forecast developed by the authors and presented in [10]. The proposed long-term risk management tool aims to find the "unknown optimal" portfolio in function of the risk aversion factor (λ) of the producer that maximizes the expected return and, simultaneously, allows the practice of the hedge against the market price volatility. To achieve this, the decision-support system maximizes a mean variance utility function (U) of the total return (π).

In this risk management tool was used a portfolio model based on utility functions instead of option pricing models [18, 19] because financial markets on electricity markets are incomplete (hedging instruments unavailable).

Uncertainties associated to generators 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 power market exercise 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 energy 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 a forward or futures contracts. Based on that, the delivery price of these mentioned contracts should be equal to the expected spot market price for the delivery period, which not always happens. Consequently, we conclude that electricity markets are not complete, and so risk attitudes and mean-variance frontiers are still relevant.

Due to the complexity of the risk management tool, we make use of Particle Swarm Optimization (PSO) to find the optimal solution.

PSO performance has been evaluated by comparing it with a Genetic Algorithm (GA) [20, 21] to show that PSO is a very successful meta-heuristic technique for this particular problem.

The paper is organized as follows: in Section II, a short overview of PSO meta-heuristic is presented; in Section III contracts are presented and how their revenues are calculated; in Section IV the problem formulation of the risk management model is presented; in Section V a case study is presented and Section VI presents some relevant conclusions.

2 PARTICLE SWARM OPTIMIZATION

Particle swarm optimization [12, 15] is an evolutionary computational algorithm inspired on a natural system. On a given iteration, a set of solutions called "particles" move around the search space from one iteration to another accordingly 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

$$X_i^{new} = X_i + V_i^{new}$$

where,

X_i^{new}	represents the new position of the particle i
X_i	represents the current position of the particle i
V_i^{new}	represents the new velocity of the particle i

$$V_i^{new} = dec(t)\cdot V_i + rand_{i,k}\cdot\alpha_{i,k}\cdot(pbest_i - X_i) + rand_{i,j}\cdot\alpha_{i,j}\cdot \\ .\left[pbest(gbest) - X_i\right]$$

where,

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

3 CONTRACTS

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:

$$r_{i,j}^{ss} = MCP_{i,j} \times e_i^{ss}$$

where,

$r_{i,j}^{ss}$	represents the revenue, in Eur, of the short position obtained by the producer in the spot market, for period i and scenario j
$MCP_{i,j}$	represents the Market Clearing Price, in Eur/MWh, for period i and scenario j
e_i^{ss}	represents the 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 of 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:

$$r^{sf} = k^{sf} \times e^{sf}$$

where,

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

In our method, the delivery period in forward contracts is the same of all period in analysis.

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 have financial settlement. There is 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 were 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 hours for Base Load Futures Contracts or equal to the simple average of the prices for the hours between 8:00 AM and 20:00 PM 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 modelling 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 [16]. 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 *MCP* is greater than the exercise price. In our method, the delivery period in call options is the same of all period in analysis.

The payoff for the short call position is given by:

$$Payoff_{i,j}^{sc} = e^{sc} \times \left[\min(k^{sc} - MCP_{i,j}, 0) + p^{sc} \right]$$

where,

$Payoff_{i,j}^{sc}$	represents the payoff, in Eur, of the short call position, for the period i and scenario j
p^{sc}	represents the premium, in Eur/MWh, of the call option
k^{sc}	represents the delivery price, in Eur/MWh, of the call option
$MCP_{i,j}$	represents the Market Clearing Price, in Eur/MWh, for the period i and scenario j
e^{sc}	represents the 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 *MCP* is lower than the exercise price.

The payoff for the long put position is given by:

$$Payoff_{i,j}^{lp} = e^{lp} \times \left[\max(k^{lp} - MCP_{i,j}, 0) - p^{lp} \right]$$

where,

$Payoff_{i,j}^{lp}$	represents the payoff, in Eur, of the long put position, for period *i* and scenario *j*
p^{lp}	represents the premium, in Eur/MWh, of the put option
k^{lp}	represents the delivery price, in Eur/MWh, of the put option
$MCP_{i,j}$	represents the Market Clearing Price, in Eur/MWh, for period *i* and scenario *j*
e^{lp}	represents the energy, in MWh, associated to the long put position obtained by the producer.

From the last equation it is clear that the long put position payoff is positive only if the *MCP* is higher than the exercise price.

4 OPTIMIZATION PROBLEM

To find optimal energy quantities establishing on each contract type, it was developed an optimization problem based on a mean-variance of the return. This formulation allows finding the optimal energy quantities that maximizes the profits and simultaneously practices the hedge against the *MCP* volatility in function of the producer risk aversion factor.

The mathematical formulation is stated as follows:

Maximize $\quad U(\pi) = E(\pi) - \lambda \times Var(\pi)$

Subj. to:

$$e_{min} \le e_i^{cs} + e^{cf} \le e_{max}$$

$$e_i^{cs}, e^{cf}, e^{cc}, e^{lp} \ge 0$$

where,

$$E(\pi) = E\left(\pi^{máx}\right) + E\left(\pi^{min}\right)$$

and,

$$Var(\pi) = \sum_{i=1}^{2}\sum_{j=1}^{2} cov_{i,j}\left(\pi^{máx}, \pi^{min}\right)$$

with,

$$\pi^{máx} = \left[\pi_1^{máx}, ..., \pi_T^{máx}\right]$$

and,

$$\pi^{min} = \left[\pi_1^{min}, ..., \pi_T^{min}\right]$$

where,

π	represents the producer return, in Eur, for the entire period in analysis
$E(\pi)$	represents the expected value of the return, in Eur, based on the forecasted price interval for the entire period in analysis
$Var(\pi)$	represents the variance of the return, in Eur, based on the forecasted price interval for the entire period in analysis
$\mathrm{cov}_{i,j}\left(\pi^{max}, \pi^{min}\right)$	represents the element *(i,j)*, in Eur, of the covariance matrix of the returns for all periods *i* based on maximum and minimum price forecast
π_i^{max}	represents the period *i* return, in Eur, based on the maximum price forecast
π_i^{min}	represents the period *i* return, in Eur, based on the minimum price forecast
T	represents the number of the considered periods for the entire period in analysis
λ	represents the producer risk aversion factor
e_{min}	represents the minimum energy, in MWh, that the producer can produce
e_{max}	represents the maximum energy, in MWh, that the producer can produce
e_i^{ss}	represents the energy amount, in MWh, that the producer decides to sell on the spot market for period *i*
e^{sf}	represents the energy amount, in MWh, that the producer decides to sell in forward contracts
e^{sc}	represents the energy, in MWh, associated to the short call position obtained by the producer
e^{lp}	represents the energy, in MWh, associated to the long put position obtained by the producer.

The mean-variance formulation resemble closely the Value-at-Risk (*VaR*) formulation and have as main advantage to be computationally more efficient for a given risk aversion factor λ. Moreover, *VaR* formulation needs higher order of information about the joint probability distribution of the payoffs and is highly sensitive to the high impact of low probability events, which create “fat tails” in payoff distribution. In this formulation we assumed the risk aversion factor λ is equal for the whole period in analysis.

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

Mathematically, the return π is given by:

$$\pi_{i,j} = r_{i,j}^{ss} + r^{sf} + P_{i,j}^{sc} + P_{i,j}^{lp} - C_{i,j}$$

with,

$$C_{i,j} = C(e_i^{ss} + e^{sf})$$

Options contracts have financial settlement; the total production cost is only dependent on the energy that the producer will sell on spot market, and on forward contracts, meaning that is only dependent of the energy established on contracts with physical settlement.

A. Penalty functions

Due to optimization problem complexity, PSO was used to find the optimal solution and results were compared with GA results.

To satisfy constraint the first restriction of the optimization problem for each period *i*, was added the following penalty function:

$$p_{f1} = \begin{cases} 0 \quad if \quad e \geq e_{min} \; and \; e \leq e_{max} \\ e^{100 \times d^2} - 1 \quad otherwise \end{cases}$$

where,

$$d = min\left[\left|e - e_{min}\right|, \left|e - e_{max}\right|\right]$$

To guaranty that all variables are positives, was added the following penalty function:

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

where,

$$e = \left|e_i^{ss,sf,sc,lp}\right|$$

B. PSO and GA Parameters

The main parameters of PSO and GA, used finding the best solution are presented in table 1 and table 2, respectively.

Besides these parameters being dependent on the fitness function, experimentations show that the number of evaluations used does not compromise the results.

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	0.2
Maximum velocity (V_{max})	0.1

Table 1. PSO Parameters

Population size	50
Nº. of generations	8000
Nº. of evaluations	400000
Crossover rate	0.8
Mutation rate	0.2

Table 2. GA Parameters

C. Producer Characteristics

It was assumed that producer cost function is equal for the entire period in analysis (one year) and is given by:

$$C(P_g) = 100 + 0.3 \times P_g + 0.02 \times P_g^2$$

where.

P_g in MW, C in Eur/h, P_g^{max} = 200 MW and P_g^{min} =5 MW.

The cost of sales (like taxes, market commissions and others) is not addressed. Moreover, there is just as much risk in the cost of sales as there is in the generation of revenue.

D. Contracts Characteristics

Options contracts characteristics with delivery period for the year 2007 are presented in Table 3.

	Exercise Price (Eur/MWh)	Premium (Eur/MWh)
Short Call	42.00	2.50
Long Put	45.00	5.00

Table 3. Options Contracts Characteristics

It was assumed that forward contracts with delivery period for the year 2007 are traded at a price equal to 40 Eur/MWh.

5 CASE STUDY

In this case a producer aims (in December 2006) to find the optimal contracts portfolio for the entire year of 2007. However, although to be beyond the purpose of this work, the producer must adjust its contractual positions continuously (say once a month) and whenever he needs to reconsider his contractual positions already established in forward and other contracts, before adjusting the portfolio.

Using the method presented in [10], that also makes use of PSO, the monthly price range average forecast for the year 2007 is shown on figure 1.

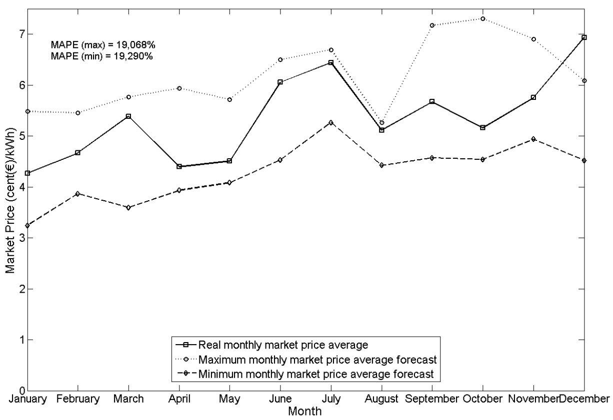

Figure 1. Monthly Market Price Range Forecast for the Year 2007 in Mainland Spanish Market, with Confidence Level of α=95%

An evaluation of PSO and GA performance for this particular problem has been carried out. The algorithms' stopping criterion was the maximum number of evaluations (fixed in 400,000 evaluations). With 20 particles in the PSO 20,000 iterations were performed. For GA a population size of 50 individuals and 8,000 generations was used. Due to random initialization, the trajectory for each run is different; so, we used 10 runs to calculate the average and the standard deviation of the results.

Due to the problem complexity, the entire period was divided in sub-periods of one month of duration allowing reducing the number of variables and, consequently, turning the optimization problem lighter.

As results, table 4 and table 5 present the average quantities, in MWh, for each contractual position and risk aversion factor, using PSO and GA, respectively.

Position	Average Quantity (MWh)			
	λ=0	**λ=1**	**λ=2**	**λ=3**
Short Spot	2.1×10^6	1.2×10^6	9.9×10^5	7.7×10^5
Short Forward	2.7×10^3	6.4×10^5	5.9×10^5	3.8×10^5
Short Call	0.839	1.3×10^6	1.4×10^6	5.4×10^5
Long Put	0.250	6.9×10^5	1.3×10^6	7.2×10^5

Table 4. Average Quantities, in MWh, to Establish by Contractual Position and Risk Aversion Factor using PSO

Position	Average Quantity (MWh)			
	λ=0	**λ=1**	**λ=2**	**λ=3**
Short Spot	1.8×10^6	1.1×10^6	1.3×10^6	1.1×10^6
Short Forward	2.4×10^5	5.4×10^5	4.4×10^5	4.8×10^5
Short Call	145.017	8.7×10^5	1.4×10^6	1.0×10^7
Long Put	444.929	9.8×10^5	7.8×10^5	4.1×10^5

Table 5. Average Quantities, in MWh, to Establish by Contractual Position and Risk Aversion Factor using GA

The results standard deviation using PSO and GA is presented in table 6 and table 7, respectively.

Position	Quantities Std. Deviation (MWh)			
	λ=0	**λ=1**	**λ=2**	**λ=3**
Short Spot	0.004	2.026	112.788	24.277
Short Forward	1.7×10^{-4}	1.028	6.233	0.979
Short Call	6.1×10^{-6}	26.243	7.797	30.443
Long Put	8.6×10^{-6}	45.682	75.483	5.041

Table 6. Quantities Std. Deviation, in MWh, to Establish by Contractual Position and Risk Aversion Factor using PSO

Position	Quantities Std. Deviation (MWh)			
	λ=0	**λ=1**	**λ=2**	**λ=3**
Short Spot	213.693	6.267	227.004	321.845
Short Forward	17.807	1.534	2.237	5.292
Short Call	0.0079	68.864	29.499	159.678
Long Put	0.0229	145.471	94.215	9.6719

Table 7. Quantities Std. Deviation, in MWh, to Establish by Contractual Position and Risk Aversion Factor using GA

Comparing the standard deviation for each solution (table 6 and table 7), we conclude that PSO is more robust than the GA.

The mean and the standard deviation of the fitness functions for the 10 runs and for each risk aversion factor are presented in table 8. Table 8 also includes the mean time necessary to reach the optimal solution for PSO and GA.

It can be verified from table 8 that, for this particular problem, PSO is faster than GA (smaller mean time), finds better solutions (smaller mean fitness value) and is more robust (smaller standard deviation). These simulations were made on an ASUS L5GX laptop, P4 3.2 GHz processor and 1 GB of memory.

Algorithm	Mean Fitness Value	Std. Fitness Value	Mean Time (sec.)
PSO (λ=0)	1.3639×10^{7}	10.9801	113.1464
GA (λ=0)	1.3181×10^{7}	2.9971×10^{5}	858.5784
PSO (λ=1)	9.5269×10^{6}	1.8706×10^{5}	107.2944
GA (λ=1)	7.8527×10^{6}	7.4777×10^{5}	885.0692
PSO (λ=2)	7.5300×10^{6}	2.6324×10^{5}	107.4961
GA (λ=2)	1.8101×10^{6}	2.3825×10^{6}	880.0213
PSO (λ=3)	6.3729×10^{6}	2.7286×10^{5}	106.3816
GA (λ=3)	4.6687×10^{6}	4.5523×10^{5}	868.8086

Table 8. PSO and GA Fitness Function Comparison

Because PSO achieve better results in this particular problem, in figure 2 and figure 3 is presented its results for the expected return and the associated risk for each month, as function of the risk aversion factor λ, respectively.

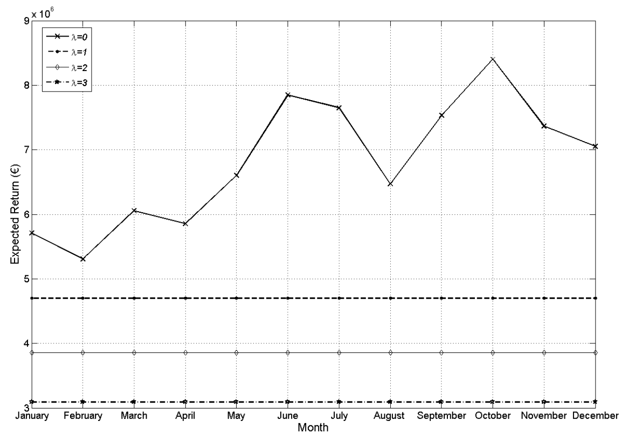

Figure 2. Producer Expected Return in Function of Risk Aversion Factor λ

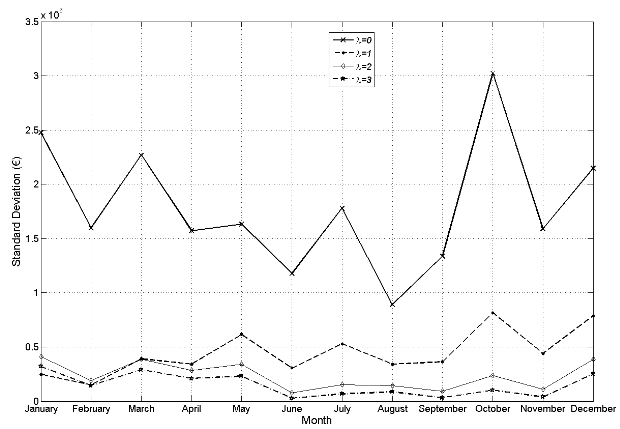

Figure 3. Risk in Function of the Risk Aversion Factor λ

From figure 2 and figure 3 we conclude that, for the same risk aversion factor λ, the bigger the expected return the bigger the risk (standard deviation of the return) that the producer is exposed to. Analyzing figure 2 and figure 3 we verify that 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. This happens because the lower the risk aversion factor the most indifferent the producer will be to the risk and therefore he will have more risky attitudes and sell more energy on the spot market, as it can be seen in figure 4.

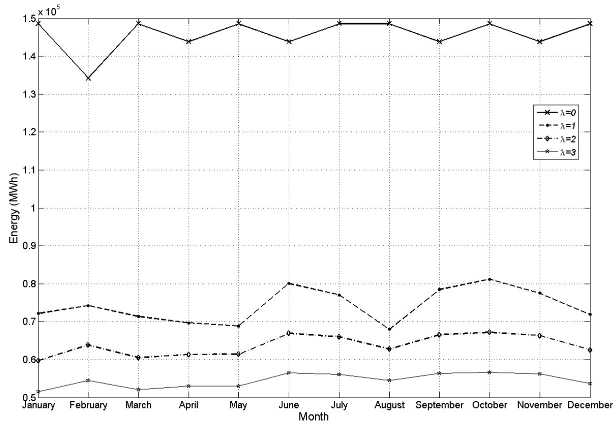

Figure 4. Optimal Energy Quantities that Producer Should Sell in Spot Market in Function of Risk Aversion Factor λ

6 CONCLUSIONS

With electricity markets liberalization, long-term contractual decisions are more difficult on an efficient risk management.

This paper proposed a new long-term risk management tool, which allows maximizing the producers expected return while practicing the hedge against spot price volatility based on the risk aversion factor.

Due to the optimization problem complexity, a Particle Swarm Optimization (PSO) meta-heuristic technique has been used. Its performance has been evaluated by its comparison with a Genetic Algorithm (GA) based approach. Actually the authors work in the application of Ant Colony System (ACS) Algorithm to solve the optimization problem with the aim to compare its results with the PSO performance, and the comparison will be reported shortly.

However, every risk management tools needs an efficient price forecast methodology. Trying to give an answer to that need a regressive model was used which enables the electricity market agents to forecast the monthly market price average range up to one year into the future. This model may find the price range value, with a certain confidence level, based on historical statistical data. The main advantage of this method is the fact that it does not make any statistical assumption relating to the market price distribution function.

Based on the results, it was proven that Particle Swarm Optimization (PSO) has significant advantages compared with GA in terms of robustness and computation time based in simulation results.

REFERENCES

[1] C. P. Rodriguez and G. J. Anders, "Energy Price Forecasting in the Ontario Competitive Power System Market", *IEEE Transactions on Power Systems*, vol. 19, no. 1, February 2004.

[2] H. Chen, C. Cañizares and A. Singh, "ANN-based Short-Term Load Forecasting in Electricity Markets", *Power engineering Society Winter Meeting*, IEEE, vol. 2, February 2001.

[3] B. R. Szkuta, L. A. Sanabria and T. S. Dillon, "Electricity Price Short-Term Forecasting Using Artificial Neural Networks", *IEEE Transactions on Power Systems*, vol. 14, no. 3, August 1999.

[4] F. Azevedo and Z. A. Vale, "Short-term Price Forecast from Risk Management Point of View", *13th International Conference on Intelligent Systems Application to Power Systems – ISAP 2005*, Arlington – EUA, November 2005.

[5] F. Azevedo e Z. A. Vale, "Forecasting Electricity Prices with Historical Statistical Information using Neural Networks and Clustering Techniques", *PSCE – Power Systems Conference and Exposition*, Georgia Atlanta –USA, October 2006.

[6] T. Niimura, H. Ko and K. Ozawa, "A Day-Ahead Electricity Price Prediction Based on a Fuzzy-Neuro Autoregressive Model in a Deregulated Electricity Market", *Proceedings of the 2002 International Joint Conference on Neural Networks*, vol. 2, pp. 12-17, May 2002.

[7] L. Hongjie, W. Xiugeng, Z. Weicun and X. Guohua, "Market Clearing Price Forecasting Based on Dynamic Fuzzy System", *Proceedings of the 2002 International Conference on Power System Technology*, vol. 2, pp. 13-17, October 2002.

[8] J. Contreras, R. Espínola, F. J. Nogales and A. J. Conejo, "ARIMA Models to Predict Next-Day Electricity Prices", *IEEE Transactions on Power Systems*, vol. 18, no. 3, February 2003.

[9] F. J. Nogales, J. Contreras, A. J. Conejo and R. Espínola, "Forecasting Next-Day Electricity Prices by Time Series Models", *IEEE Transactions on Power Systems*, vol. 17, no. 2, May 2002.

[10] F. Azevedo, Z. A. Vale e P. B. Moura Oliveira, "Long-term Price Range Forecast Applied to Risk Management Using Regression Models," *Proceedings ISAP 2007 - 14th International Conference on Intelligent Systems Application to Power Systems*, Kaohsiung - Taiwan, November 2007.

[11] J. Kennedy and R. Eberhart, "Particle Swarm Optimization", *IEEE International Conference on Neural Networks*, Perth, Australia, 1995.

[12] Y. Shi and R. Eberhart, "Parameter Selection in Particle Swarm Optimization", *Proceedings of the Seventh Annual Conference on Evolutionary Programming*, pp. 591-601, 1998.

[13] R. Bjorgan, C. Liu and J. Lawarrée, "Financial Risk Management on a Competitive Electricity Market", *IEEE Transactions on Power Systems*, vol. 14, no. 4, November 1999.

[14] S. Makkonen, R. Lahdelma, A. Asell and A. Jokinen, "Multi-criteria Decision Support in the liberalized Energy Market", *Journal of Multi-Criteria Decision Analysis*, Anal. 12:27 – 42, 2003.

[15] E. Tanlapco, J. Lawarrée, and C. Liu, "Hedging With Futures Contracts in a Deregulated Electricity Industry", *IEEE Transactions on Power Systems*, vol. 17, no. 3, August 2002.

[16] R. Bjorgan, H. Song, C. Liu and R. Dahlgren, "Pricing Flexible Electricity Contracts", *IEEE Transactions on Power Systems*, vol. 15, no. 2, May 2000.

[17] J. Conejo, F. J. Nogales and J. M. Arroyo, "Price-Taker Bidding Strategy Under price Uncertainty", *IEEE Transactions on Power Systems*, vol. 17, no. 4, November 2002.

[18] F. Black and M. Scholes, "The Pricing of Options and Corporate Liabilities", *Jornal of Political Economy*, no. 81, pp. 637 – 659, June 1973.

[19] R. C. Merton, "Theory of Rational Option Pricing", *Bell Journal of Economics and Management Science*, no. 4, pp. 141 – 183, 1973.

[20] J. Holland, "Genetic algorithms," *Scientific American*, pp. 66 – 72, July de 1992.

[21] M. Mitchell, "An Introduction to Genetic Algorithms," *MIT Press*, 1996.