Multi-agent optimization of electricity markets participation portfolio with NPSO-LRS

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Abstract. The increasing unpredictability of electricity market prices as reflection of the renewable generation variability brings a new dimension to risk formulation, since market participation risk should consider the prices variation in each market. This paper proposes a new portfolio optimization model, considering a new approach for risk management. The problem of electricity allocation between different markets is formulated as a classic portfolio optimization problem with the consideration of the market prices forecast error as integral part of the risk asset. The multi-objective problem leads, however, to a heavy computational burden, and for this reason the method of weighting single-criterion objectives is applied in this paper. A particle swarm optimization-based metaheuristic is applied in order to enable decreasing the execution time of the optimization, while guaranteeing a good quality of results. A case study based on real data from the Iberian electricity market demonstrates the advantages of the proposed approach to increase market players' profits while minimizing the market participation risk.

Keywords: Agent-based simulation, Decision support, Electricity markets, Portfolio optimization, Swarm Intelligence

1 Introduction

Energy markets offer different forms and possibilities for negotiating electricity. In the US, most EM work with a bid optimization mechanism [1]. European countries have a way of operating based on symmetrical and asymmetric models [2]. Usually all markets also support the possibility of electricity trading through bilateral contracts. However, different markets with distinct characteristics tend to become increasingly similar in order to facilitate the transaction of electricity between them and build unified global markets [3].

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A relevant step towards the creation of a unified continental market in Europe has recently been implemented through the Price Coupling of Regions (PCR) initiative [4]. This advance has emerged from the implementation of EU policies aiming at creating a common internal market for electricity in Europe [5]. This combination of markets allows for large-scale transactions of electricity and also allows the efficient use of renewable-based energies that can be commercialized to be consumed far away from their production [6].

Understanding the behavior of EM is essential for all players, as this knowledge enables making an efficient operation in EM [7]. In this scope, the use of modeling and simulation tools have increased significantly. Multi-Agent Systems (MAS), in particular, have a crucial importance in studying the behavior of EM, using an artificial intelligence approach to simulate EM [8]. MAS simulations are also relevant for decision support in strategic EM participation. MASCEM (Multi-Agent Simulator of Competitive Electricity Markets) [9, 10] is MAS that allows the simulation of serval markets models, namely day-ahead pool, bilateral contracts, balancing markets and ancillary services. AiD-EM [11] (Adaptive Decision Support for Electricity Markets Negotiations) is a decision support system that has been integrated with MASCEM, allowing agents to automatically adapt their strategic behavior according to their current situation. AiD-EM provides agents with the capability of analyzing contexts of negotiation, such as the week day, the period, the particular market in which the negotiating, the economic situation and weather conditions.

This paper proposes a portfolio optimization methodology, allowing agents to decide the participation investment that should be made in each available type of market, in order to optimize the potential profits from selling their electricity. The portfolio optimization methodology considers the forecasted market prices that are expected to be found in each alternative market or market session that the supported agents are allowed to participate in. A New Particle Swarm Optimization - Local Random Search (NPSO-LRS) is introduced in order to enable the large amount of market participating agents to optimize their decisions in an acceptable time, considering the objective of decision support for market participation in a real market environment.

2 Related work

In any economic activity, there is a relationship between risk and return. The correct knowledge of this relationship is fundamental for the commercial performance in a competitive environment. It becomes necessary to have a good knowledge of the investment in order to avoid unexpected risks that can make the investment unfeasible and inappropriate [12]. Each market presents different characteristics, requiring specific knowledge for the identification of risk factors.

In general, an investor (player) aims at achieving an as large as possible return on its portfolio. However, a high return is usually associated to a higher risk. Markowitz proposed [13] the first definition of the portfolio optimization problem. This work introduced a standard mean-variance model based on the assumption that the investor is risk averse and that the return of assets is normally distributed. In most approaches, the portfolio optimization problem formulation can be either directed to minimize the risk, or otherwise maximize the return, thus leading to a multi-objective problem with two different fitness functions. Usually the transformation of two objectives function into one (single-criterion objectives) is made. This method is used in [14–16]. When the transformation into one fitness function is made it is necessary to consider a trade-off coefficient ranging between 0 and 1. The investor (agent) can then choose the portfolio depending on specific risk/return requirements.

3 Multi-agent simulation of competitive electricity markets

MASCEM [9, 17] aims to facilitate the study of complex electricity markets. It considers the most important entities and their decision support features, allowing the definition of bids and strategies, granting them a competitive advantage in the market. Players are provided with biding strategic behavior so they are able to achieve the best possible results depending on the market context. MASCEM players include: market operator agents, independent system operator agents (ISO), market facilitator agents, buyer agents, seller agents, Virtual Power Player (VPP) [17] agents, and VPP facilitators.

MASCEM allows the simulation of the main market models: day-ahead pool (asymmetric or symmetric, with or without complex conditions), bilateral contracts, balancing market, forward markets and ancillary services. Hybrid simulations are also possible by combining the market models mentioned above. Also, the possibility of defining different specifications for the market mechanisms, such as multiple offers per period per agent, block offers, flexible offers, or complex conditions, as part of some countries' market models, is also available. Some of the most relevant market models that are fully supported by MASCEM are those of the Iberian electricity market – MIBEL, central European market – EPEX, and northern European market – Nord Pool. Some other market types can be provided by different external systems, by using an upper-ontology, which defines the main concepts that must be understood by agents that participate in power systems and electricity markets' related simulations.

Simulation scenarios in MASCEM are automatically defined, using the Realistic Scenario Generator (RealScen) [18]. RealScen uses real data that is available online, usually in market operators' websites. The gathered data concerns market proposals, including quantities and prices; accepted proposals and established market prices; proposals details; execution of physical bilateral contracts; statement outages, accumulated by unit type and technology; among others. By combining real extracted data with the data resulting from simulations, RealScen offers the possibility of generating scenarios for different types of electricity markets. Taking advantage on MASCEM's ability to simulate a broad range of different market mechanisms, this framework enables users to consider scenarios that are the representation of real markets of a specific region; or even consider different configurations, to test the operation of the same players under changed, thoroughly defined scenarios [18]. When summarized, yet still realistic scenarios are desired (in order to decrease simulations' execution time or facilitate the interpretation of results), data mining techniques are applied to define the players that act in each market. Real players are grouped according to their characteristics' similarity, resulting in a diversity of agent types that represent real market participants.

In order to allow players to automatically adapt their strategic behavior according to the operation context and with their own goals, a decision support system has been integrated with MASCEM. This platform is ALBidS (Adaptive Learning Strategic Bidding System) [11], and provides agents with the capability of analyzing contexts of negotiation, allowing players to automatically adapt their strategic behavior according to their current situation. In order to choose the most adequate strategy for each context, ALBidS uses reinforcement learning algorithms (RLA), and the Bayesian theorem of probability. The contextualization is provided by means of a context definition methodology, which analyzes similar contexts of negotiation (*e.g*. similar situations in the past concerning wind speed values, solar intensity, consumption profiles, energy market prices, and types of days and periods, *i.e.* business days *vs.* weekends, peak or off-peak hours of consumption, etc.). This contextualization allows RLAs to provide the most adequate strategic support to market players depending on each current context. ALBidS strategies include: artificial neural networks, data mining approaches, statistical approaches, machine learning algorithms, game theory, and competitor players' actions prediction, among othersALBidS is implemented as a multi-agent system itself, in which each agent is responsible for an algorithm, allowing the execution of various algorithms simultaneously, increasing the performance of the platform. It was also necessary to build a suitable mechanism to manage the algorithms efficiency in order to guarantee the minimum degradation of MASCEM execution time. For this purpose, a methodology to manage the efficiency/effectiveness (2E) balance of ALBidS has been developed [11].

4 Proposed methodology

The proposed portfolio optimization consists of finding a set of actions that make the market share the most advantageous as possible for a supported market player, this player can be a single producer or an aggregator [19]. These actions include the sale and purchase of electricity, which may occur within the same market and time period, depending on the characteristics of each market. The characteristics of the problem, such as considering the transaction prices dependent on the negotiated amount, and the multi-period approach, make the problem non-linear and thus difficult to solve with exact methods in acceptable time frames. For this reason and considering that the objective of this methodology is to be used as decision support of market players' actions in real or realistic scenarios, a PSO based approach is applied to solve this problem in a smaller execution time. This section presents the problem formulation as well as the algorithm used to solve it.

4.1 Mathematical formulation

As previously described, the proposed model includes two objective functions: one is a maximization and the other a minimization. In order to solve the problem, we have chosen to formulate the problem so that the objective function is a weighted sum of the objectives. The main advantages of this method are the simplicity in implementation and use, and its efficiency of computational time. The main disadvantages are the difficulty to determine the appropriate weight coefficients to be used, and the necessity for a proper scaling of the objectives, which requires a considerable amount of extra knowledge about the problem. Another problem is that it cannot obtain all the points of the Pareto front, as it is dependent on the weights combination that is used. However, the weighted approach is adequate for decision making in real world problems due to its faster execution time and can also be very useful to get a preliminary results of the Pareto front of a certain problem or to provide priori information to be exploited by another approach.

Profit formulation

The formulation of the profit maximization problem is based on the model presented by the authors in [20]. $Spow_{M,d,p}$ and $Bpow_{M,d,p}$ represent the decision variables for the problem – the amount to sell and buy in each market session in each time period, as in (1).

$$f1(Spow_{M \ldots NumM}, Bpow_{M \ldots NumM}) = \begin{bmatrix} \sum_{M=M1}^{NumM} \left(Spow_{d,p,M} \times pS_{M,d,p} \times Asell_M\right) - \\ \sum_{M=M1}^{NumM} \left(Bpow_{d,p,M} \times pB_{M,d,p} \times Abuy_M\right) - \\ \sum Cost_{d,p}^{TEP} \end{bmatrix} \tag{1}$$

Where:

- $Asell_M$ and $Abuy_M$ represent the indication if this player can enter in negotiation in market M, and are boolean variables;
- $Cost$ represents the function of production costs;
- TEP represents the total electricity produced;
- $Spow_{d,p,M}$ represents the amount of electricity to sell in market M;
- $Bpow_{d,p,M}$ represents the amount of electricity to buy in market M;
- $NumM$ represents the number of markets.

Considerations:

$$\forall d \in Nday, \forall p \in Nper, Asell_M \in \{0,1\}, Abuy \in \{0,1\} \tag{2}$$

$$pS_{M,d,p} = \begin{cases} Forecast_{M,d,p}^{ANN} & if\ M \notin bilateral\ contacts \\ Value\left(Spow_{d,p,M}\right) & if\ M \in bilateral\ contacts \end{cases} \tag{3}$$

$$pB_{M,d,p} = \begin{cases} Forecast_{M,d,p}^{ANN} & if\ M \notin bilateral\ contacts \\ Value\left(Bpow_{d,p,M}\right) & if\ M \in bilateral\ contacts \end{cases} \tag{4}$$

$$TEP = \sum Energy_{prod} \quad (5)$$

$$Energy_{prod} \in \{Renew_{prod}, Therm_{prod}\} \quad (6)$$

$$Cost_{d,p}^{TEP} = a \times Therm_{prod}{}^{2} + b \times Therm_{prod} + c \quad (7)$$

Where:

- $Nday$ represents the member of days;
- $Nper$ represents the number of periods (1 hour per period);
- $Forecast_{M,d,p}^{ANN}$ represents the price forecasting value of ANN for market M, day d, and period p;
- $Value(Spow_{d,p,M})$, $Value(Bpow_{d,p,M})$, represent the values of price for amount electricity in bilateral contracts;
- $Energy_{prod}$ represents the electricity produced by the player;
- $Renew_{prod}$ represents the renewable electricity produced;
- $Therm_{prod}$ represent the thermoelectric electricity produced;
- a, b and c represents the coefficients of total cost.

In expression (3) and (4) if the considered market does not work by means of bilateral negotiations, the expected transaction prices in each market session at each time are obtained through the application of Artificial Neural Network (ANN) [21], On the other hand, if the negotiation is performed through bilateral agreements, the price of electricity is highly variable depending on the amount of traded electricity. This characteristic is addressed through a forecasting and estimation methodology based on fuzzy logic and clustering [22]. From expression (6) it is possible to see that this model considers electricity produced from renewable electricity and from thermoelectric plants. Equation (7) shows the calculation for the cost of thermoelectric production.

Expression (8) represents the association between the amount of traded electricity and the corresponding price, which is obtained through fuzzy logic.

$$Value(Spow_{d,p,M} \text{ or } Bpow_{d,p,M}) = Data(fuzzy(pow))_{d,p,M} \quad (8)$$

Where:

- pow – represents the negotiation amount;
- $Data$ – historical data used to create the fuzzy variables;
- $fuzzy$ – represents the fuzzy variable built for market M, day d, and period p.

This paper applies the methodology proposed and validated in [23]. The method is based on the development a dynamic fuzzy variable that approximates the values of contract prices for different negotiated electricity amounts. In (8), $Data$ represents the historical data referring to the period in which the price estimation is established. These historical data in this case are grouped by days and periods, and in this case the created fuzzy will use data that refer to this to the period and day in question. For each period of each day of each market fuzzy membership functions are estimated. The number of membership functions is obtained by applying the K-means clustering technique [24].

Constraints:

$$\sum_{M=M1}^{NumM} Spow_M \leq TEP + \sum_{M=M1}^{NumM} Bpow_M \tag{9}$$

$$0 \leq Renew_{prod} \leq Max_{prod}^{Renew} \tag{10}$$

$$Min_{prod}^{Therm} \leq Therm_{prod} \leq Max_{prod}^{Therm}, if\ Therm_{prod} > 0 \tag{11}$$

$$0 \leq TEP \leq TEP_{max} \tag{12}$$

Where:

- Max_{prod}^{Renew} – corresponds to the maximum limit for renewable production;
- Min_{prod}^{Therm} and Max_{prod}^{Therm} – corresponds respectively to the maximum and minimum limit for thermoelectric production.

The main constraint is expressed in (9), to impose that the total electricity reserved to be sold in the set of all markets is never higher than the total expected production TEP of the player, plus the bought electricity in all markets in the same time period. The other constraints are more specific for the characteristics of each player; it should be noted that if the player is a thermoelectric generator, it should either not produce at all, or produce at least a minimum value, because it is not possible to operate under a minimum technical limit. Constraint (11) expresses this condition. Further constraints can be added to the problem, particularly of more technical nature.

Weighted sum formulation

The function presented in equation (13) considers the fitness function, where $f1$ represents the return (1) and $f2$ represents the risk. This formulation considers two objectives: maximizing profit and minimizing the risk. These are represented through two objective functions that depend on each other. Thus, as proposed in [14] we construct a single objective function (13) with a trade-off parameter λ, which is imposed by the user.

$$Max\left[\lambda \times \left(f1(Spow_{M \ldots NumS}, Bpow_{M \ldots NumM})\right) - (1-\lambda) \times \left(f2\left(Risk_{d,p}\right)\right)\right] \tag{13}$$

Where:

- λ – represents the trade-off and $\in\ [0; 1]$
- $Risk_{d,p}$ – represents the value of risk in p period and d day.

The function of equation (13) is based on single-criterion objectives; the fitness function is composed of two equations, and provides the results for each period of each day. When λ is 1 the model maximizes the expected return of the portfolio. On the other hand, when λ is near to 0, the model minimizes the risk of the portfolio. So, we can say that the sensitivity of the player to the risk increases as λ approaches unity, while it decreases as λ approaches zero. Equation (14) shows the risk calculation methodology.

$$f2(Risk_{d,p}) = \begin{bmatrix} \sum_{M=M1}^{NumM} (Spow_{M,d,p} \times pS_{M,d,p} \times error_{M,d,p}) + \\ \sum_{M=M1}^{NumM} (Bpow_{M} \times pB_{M,d,p} \times error_{M,d,p}) \end{bmatrix} \tag{14}$$

Where:

- $error_{M,d,p}$ represent the error for market M, day d and period p.

As can be seen by (14), the risk is calculated based on the price forecasting error in each market, at each time. It is expected that the allocation of resources (electricity sale or purchase) is made depending on the error; thus, if the error in a certain market in a given time period has a high value, the allocation will be lower. If the error is smaller, the allocation will be higher (if the expected price is attractive to generate a good income). This also takes into account the value of the trade-off, if this value is near 1, the allocation is done with big level of risk, on the other hand if the value is small the risk is taken into account and the return will be lower. The error calculation is performed as in (15).

Consideration:

$$error_{M,d,p} = \begin{cases} ANN_{M,d,p}^{error} & if\ M \notin bilateral\ contacts \\ Fuzzy_{M,d,p}^{error} & if\ M \in bilateral\ contacts \end{cases} \tag{15}$$

Where:

- $ANN_{M,d,p}^{error}$ – is the training error of ANN for market M, day d, and period p;
- $Fuzzy_{M,d,p}^{error}$ – represent the error of $Fuzzy$ application;

Depending on the market where the trading is performed we will have different levels of risk, since each market has a particular forecast. In equation (15) two types of errors are considered because two different methods for obtaining electricity prices forecasts are considered. These methods differ in view of the negotiating circumstance. The ANN [21] will be used in the case when the amount of electricity does not influence the target price; the ANN uses the specifically grouped training data, the tests and results obtained can be consulted in the above mentioned reference. The other method, based in clustering and fuzzy approaches [22] is used when the negotiated amount influences the expected price. In this case the method groups the training data by day of the week and by period, and then the different fuzzy functions are constructed for each period. The work performed with this methodology can be found in [22] as well as in [23]. As mentioned before, the market prices forecast / estimation error is used in this work to determine the risk measure. The use of this type of risk measure is a novel approach and cannot be found in the literature. The standard deviation variance of the prices' historical values has been analysed as well, since the forecast and estimation use the historical data as elements of training and test.

4.2 Swarm Optimization method

The swarm intelligence methods were firstly introduced by Kennedy and Eberhart in 1995 [25], when they presented the Particle Swarm Optimization (PSO), partly inspired by the behaviour of large swarms such as schooling or flocking birds. This algorithm does not assure the optimal global solution; generally, the search is stopped when the stopping criterion is reached.

In the original PSO, since each particle moves in the search space guided only by its best historical solution and by the best global solution, it can get stuck in an ideal local solution when the best current global solution in a great and not easy place for the particle it escapes this.

The NPSO-LRS is very similar to the standard PSO, presenting two differences, one of which is in the equation of movement and another, in fact, of performing a local search. The changes in the equation of motion of the particles are expressed in equation (16).

$$v_i^{k+1} = w^k . v_i^k + c_{1b} . r_{1b}^k . \left(Pbest_i^k - x_i^k\right) + c_{1w} . r_{1w}^k . \left(Pworst_i^k - x_i^k\right) + c_2 . r_2^k . \left(Gbest_i^k - x_i^k\right) \tag{16}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{17}$$

Where:

- k – iteration;
- i – particle;
- v_i^k – represent the velocity of particle i in the iteration k;
- v_i^{k+1} – represent the velocity of particle i in the iteration $k+1$;
- x_i^k – represent the position of particle i in the iteration k;
- x_i^{k+1} – represent the positions of particle i in the iteration $k+1$;
- $Pbest$ – best personal solution;
- $Pworst$ – worst personal position;
- $Gbest$ – best global solution;
- w – inertia term;
- c_{1b}– personal attraction to the best position;
- c_{1w} – personal attraction to the worst position;
- c_2 – global attraction term;
- r_{1b}, r_{1w} and r_2 – are random numbers, $\in [0,1]$.

The change in this aspect of the PSO is the inclusion of the variable that represents the poor experience in which the particles have passed. In this way, the most unfavorable position is stored in memory, but these positions are always valid by the constraints. With the inclusion of this new component, the research will be easier to get out of the points considered great places and reach the points very close to the global optimum.

This version of the PSO also has a component that is the LRS (local random search), where each iteration is performed a local search [26], the equation (18) and (19), define the search space that the LRS method can used.

$$x_i^{min} = lim_i^{min} + (x_i^k - lim_i^{min}) \times \beta \tag{18}$$

$$x_i^{max} = lim_i^{max} + (lim_i^{max} + x_i^k) \times \beta \tag{19}$$

$$R_i^k = x_i^{min} + x_i^{max} \tag{20}$$

$$x_i^{k+1} = x_i^k + R_i^k \times r_l \tag{21}$$

Where:

- lim_i^{min} – correspond to the minimum limit of the problem
- lim_i^{max} – correspond to the maximum limit of the problem
- β – local area parameter
- R_i^k – represent the local area modification
- r_l – random number $\in$ [-1,1]

With this add-on research method, you can make the algorithm more robust and avoid the best locations. At the end of the local search, each solution found that is better than the previous one will remain in memory and will be used at the beginning of the next search.

The inertia parameter is updated at the end of each iteration, considering the following equation called by linear decreasing inertia, equation (22):

$$w_k = w_{max} - \frac{(w_{max} - w_{min})}{k_{max}} \times k \tag{22}$$

Where:

- w_{max} – is the maximum value of inertia;
- w_{min} – is the minimum value of inertia;
- k_{max} – is the maximum value of iterations.

5 Results

This section presents the results referring to the case study. Initially the case study is described, and the results from the application of the proposed methodology is presented. The numerical results as well as the corresponding explanation are presented below.

5.1 Case study

This case study considers 1 period from a random day. 5 distinct electricity markets are considered, in which there is the possibility of selling electricity; and 4 markets for the purchase of electricity. In order to improve the analysis of the problem, the following names were given to the markets, with reference to the real markets of MIBEL[27]:

- Spot: Next-ahead market;
- Bilateral: negotiation of bilateral contracts;
- Balacing1: first session of the balancing market;
- Balancing2: second session of the balancing market;
- Smart-Grid: local market, at SG level.

Specific rules have also been created for its negotiations. In the Spot market it is only possible to sell electricity to selling agents, while in other markets it is possible to sell and buy, being established that it is possible to buy a maximum of 10 MW in each market and in total it is allowed to sell 50 MW of electricity (purchase of 10 MW in the four markets plus 10 MW of TEP). The total of 10 MW of energy produced is from renewable sources and is assumed as without financial charges, in order to facilitate the analysis of the results. In the Bilateral and Smart-Grid markets is obtained through the methodology presented in [23], and there is the possibility of buying and selling energy in the same period. In other markets, the performance of an action (purchase or sale) implies the impossibility of performing the other.

Seven different values are considered for the λ value, namely $\lambda = \{0{,}1; 0{,}15; 0{,}2; 0{,}25; 0{,}5; 0{,}75; 1\}$, this set has been chosen because considering the experiments carried out, it was concluded that this set of presented values allows a better graphic visualization of the results. **Table1** presents the NPSO-LRS parameterization that is applied in this case study. This parameterization is the combination that has achieved the best results after a preliminary sensitivity analysis.

Table 1. NPSO-LRS, parameters.

Parameter	Value
Number of Particles	10
Maximum Iterations	10000
Stopping Criterion	Sum (Variance ($Pbest$)) =1×10^{-8}
Number of Repetitions	100
c_{1b}	0.95
c_{1w}	0.25
c_2	0.80
β	0.01
w_{max}	0.9
w_{min}	0.4

5.2 Numerical results

A resolution applying a deterministic technique is presented, where the exact result is found. The execution time spent by this resolution is, however, very extensive, making it impossible to be applied in real contexts.

Table 2. Deterministic vs. metaheuristics results

Method	Time (s)		Objective Function (€)		
	Total	Mean	Maximum	Mean	STD
NPSO-LRS (Metaheuristic)	4272.7	42.727	1999.55	1687.78	114.63
Cplex (Deterministic)	43710.68		2000.65		

As can be observed by **Table 2**, the use of meta-heuristic approaches is essential in this context, as proven by the analysis of the execution time. The resolution by the exact method takes 43710.68 seconds (12.14 hours) while achieving a solution using the NPSO-LRS takes 4272.7 seconds (71.21 minutes) for the 100 runs, In **Table 2**, the values of the objective function column for metaheuristic resolution refer to 100 runs, and the mean, maximum and STD values are for this set of 100 results. Additionally, the value of the objective function has a minimum difference, about 5,48E-04 relative to the highest value (exact method).

Fig. 3 shows the efficient frontier for the 1st period. As one can see, the value of return increases according to the increase of the risk exposure value.

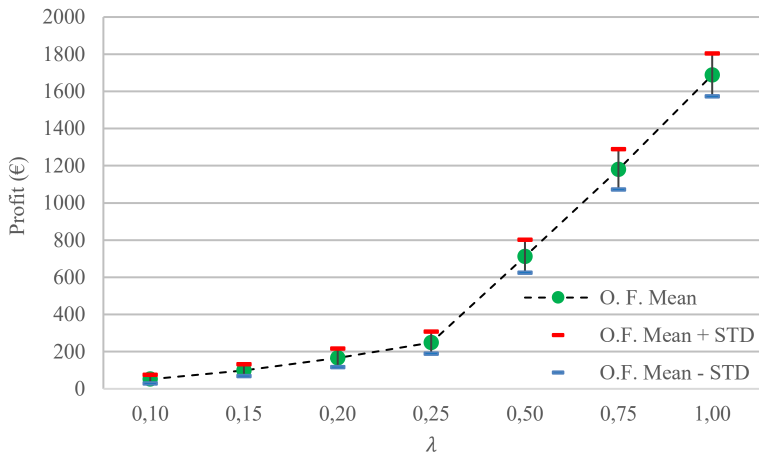

Fig. 1. Efficient frontier

As shown by **Fig. 1**, when the exposure to the risk is maximum obtain the maximum value of return, which is 1999.55 (€) and corresponds to λ = 1. **Table 3** shows the values of sales and purchases in the different considered markets. For each trade-off the allocation of electricity is made differently.

Table 3..Results for NPSO-LRS optimization

λ	Profit	Risk	Sales					Purchases				
			Spot	Bil.	Bal.1	Bal.2	S.G.	Spot	Bil.	Bal.1	Bal.2	S.G.
0.10	1363.27	33.04	23.14	0	0	0	0	0	3.14	10	0	0
0.15	1373.48	34.45	23.60	0	0	0	0	0	3.6	10	0	0
0.20	1777.97	117.39	33.88	0	0	0	0	0	3.88	10	10	0
0.25	1910.50	156.73	22.55	11.5	0	0	0	0	4.05	10	10	0
0.50	1967.00	204.63	19.53	11.5	0	0	3.35	0	4.38	10	10	0
0.75	1997.30	251.21	16.05	11.5	0	0	7	0	4.55	10	10	0
1.00	1999.55	264.04	15.56	11.5	0	0	7.94	0	5	10	10	0

Table 3 shows that the allocation of electricity increases with the exposure to risk. Since the risk is based on the forecasting error - **Fig. 2 a)**, when the risk exposure is greater, larger amounts are allocated to markets where the error is greater as well. Analyzing the example of selling in market SG (smart-grid), with λ=0.1 the player has a small exposure to the risk, which indicates that the model allocates the sales to markets where the error is smaller, which is not the case. However, when λ increases, sales are allocated in this market because the risk is less relevant. In this case, this market offers the possibility of achieving more return from the electricity sale. In the case of the spot market, with a low λ all electricity (production plus purchase) is allocated in thus market, because it has the lower amount of error that implies lower risk.

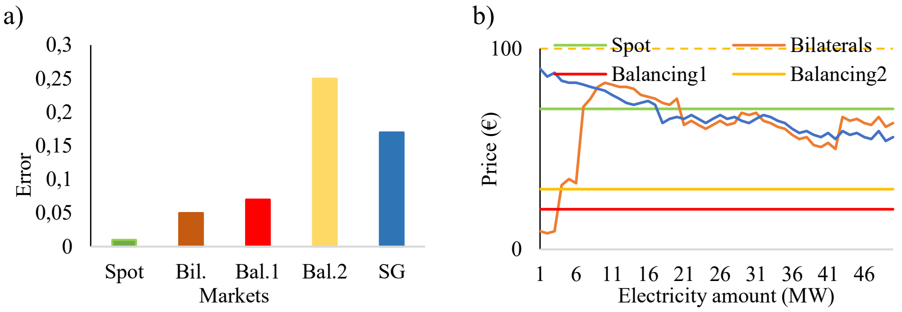

Fig. 2. a) Error values for 1st period and b) Expected prices for 1st period

The amount of electricity sold in this market with a small level of risk does not reach the maximum amount that is possible to sell, because in order to achieve that maximum amount, there is a need to buy electricity as well. Since the electricity purchase risk is also considered in the proposed model, there are no purchases (or only small amounts), in markets where the risk is high when λ is low.

6 Conclusions

This paper proposed a new model to optimize electricity market agents' participation portfolio, considering the maximization of the return and the minimization of the negotiation risk. In this work, the risk asset is modelled based on variability of market prices, through the measurement of the prices forecasting error in different markets throughout the time. A NPSO-LRS based approach is introduced to enable solving the proposed optimization problem in an acceptable execution time, so that the optimization process can be used as decision support to EM players through the integration in the AiD-EM decision support system.

Results show that the proposed NPSO-LRS model enables reaching optimization results that are very close to the optimal value (achieved by the exact method), but in a much lower execution time. In this way the proposed approach shows its advantages for application in real market participation scenarios, in which agents' decisions must be taken quickly and considering the expected behavior of a large number of competitor agents.

Future research will focus on extending the proposed model in order to consider more technical constraints, e.g. constraints on the level of renewable electricity production. Other work refers to implementing further optimization techniques to try achieving good quality of results in even smaller execution times, including distributed optimization approaches.

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