Optimization of Multiple Electricity Markets Participation using Evolutionary PSO

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***Abstract*—Electric power systems have undergone major changes in recent years. Electricity markets are one of the sectors that has been most affected by these changes. Electricity market design is being updated in order to support efficient operation and investments incentives. However, the development of efficient rules is neither easy nor guaranteed. This paper addresses the simulation of multi-participation in electric energy markets. The purpose of this simulation is to offer solutions to electricity market players, in order to support their decisions on future participation situations. For this, artificial intelligence techniques will be used, namely for forecasting and optimization processes. In specific, an optimization approach based on Evolutionary Particle Swarm Optimization (EPSO) is proposed. The achieved results are compared to those of a deterministic resolution method, and of the classical Particle Swarm Optimization (PSO). Results show that the proposed approach is able to achieve higher mean and maximum objective function results than the classical PSO, with a smaller standard deviation. The execution time is higher than using PSO, but still very fast when compared the deterministic method. The case study is based on real data from the Iberian electricity market.**

***Index Terms*— Artificial Intelligence, Decision Support, Electricity Markets, Portfolio Optimization and Swarm Optimization.**

I. INTRODUCTION

Electricity systems in developed countries are subject to a substantial transition process towards the emergence of smart grids (SG), which are affecting the current electricity markets (EM) models [1]. There are various factors that are causing changes in the SG environment, namely: environmental concerns and corresponding policies supporting renewable energies sources, concerns of security of supply including aspects of self-sufficiency, efforts to increase system efficiency, deregulation as well as considerable technological advancements [2]. However, at the political level there is a growing concern about the development of SG, the European Commission in [3], calls for a trans-European directive, that provides new and better technical foundations for distant control of highly distributed networks on an increasing large scale. The directive approach would involve new technologies for generation, networks, energy storage, load efficiency, control and communications, liberalized markets and environmental challenges, which can integrated and operate in a distributed environmental.

EM and SG are complex and dynamic environments. The complexity is increasing due to the number of new participants and the interactions between multiple stakeholders. It is possible to enumerate various participants, such as large energy generators, general consumers, interruptible consumers and storage consumers, and renewable energy producers. The dynamics are caused by the varying energy demands, changing prices and customer migrations [4]. As EM continues to evolve in a SG environment, there is a growing consensus toward developing a sophisticated computing infrastructure. The infrastructure will have to accommodate complexity requirements of operation, integration and coordination of an integrated system with two-way electric power flow. The flow of power is not only from the grid to customers, but also from customers to the grid when customers have surplus of solar, wind or any other renewable energy sources.

The distributed generation (DG) brought with it a sharp increase in electricity production despite renewable sources, but also an increment of electricity producers, namely small-scale producers. For the power systems brings advantages like, minimization of real power losses and reactive power loss, reduce power system oscillation, reduce pollution as it uses cleaner energy resources, on the other hand the DG has some limitation also like small power generation, subsidiary system to the main system, mechanical maintenance required, and choice of type of distribution systems greatly depended upon the environmental factors. In the power systems, the DG has caused the unidirectional flow that existed takes another direction and becomes bidirectional, because the consumers in this way can be also producers. This change has brought many difficulties in managing the system, but today the control power systems have evolved to respond to this problem and make the system reliable and flawless [5].

In order to provide adequate decision support to market players, it is necessary to adapt or create innovative methods for the study of electricity systems as they have undergone changes with the new SG and DG paradigms. The analysis of electrical systems performed by traditional methods, such as centralized optimization methods, are flawed due to their obsolete state

This work has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 641794 (project DREAM-GO) and No 703689 (project ADAPT) and from FEDER Funds through COMPETE program and from National Funds through FCT under the project UID/EEA/00760/2013.

978-1-5386-5583-2/18/$31.00 ©2018 IEEE

when compared to the ever-changing systems of electricity. In this way, the current panorama of electricity systems alerts to the urgency of creating simulation tools that allow supporting the system operation. The same is true in EM, since there is a need for tools to anticipate the actions of the stakeholders in the markets in order to take advantage of them. The situation that is occurring can be bought from the situation that occurred in the last decade with the deregulation process [6].

In this way, this work presents a methodology for participation in electric energy markets that provides support to EM participants, using a novel approach based on Evolutionary Particle Swarm Optimization (EPSO) [7]. After this introductory section, section II presents a review on related work, where a discussion on the portfolio optimization problem is provided. In section III the mathematical formulation that shapes participation in EM is presented. Section IV presents the EPSO methodology. In section V, the case study is described and in section VI the results are presented. Finally, section VII presents the conclusions of this work.

II. Related Work

The portfolio optimization problem consists of a portfolio selection in which the objective is to find the optimal way of investing a particular amount of money in a given set of securities assets. The theory of portfolios was introduced by Henry Markowitz in 1952, being published in an article in Journal of Finances [8]. The traditional approach to the portfolio optimization problem was initially developed for the activity on the stock exchanges, and only later has been applied to the other areas, such as the electricity markets domains. The Markowitz theory consist in portfolio efficient calculation by analyzed the average of the returns obtained over time, which is obtained by the expect value (average) resulting from the available historical cases. In this model, the risk was also included, and each action that result in return also result in a possible value which evaluate the risk incurred by this action. The risk is given by the variance of the portfolio, which measures the variance of the expected return.

There are some reports of applied portfolio optimization in EM, one of which can be found in the paper presented in [9], a study is made to efficiently combine the sources of energy present in Mexico. The author suggests that investment in wind energy should lead to higher returns without increasing the level of risk. The same author, in [10] makes use of Markowitz's theory to solve the problem of the combinations of sources of electricity generation available in the EU. In these works, the authors conclude that optimal portfolios should allocate larger investments in wind energy and other renewable sources to become efficient. This is because they are fixed-cost technologies and are not subject to changes in fuel prices.

In the literature, there are some works for solving the portfolio optimization problem using heuristic methods. Genetic Algorithm (GA) is applied to this problem in [11], [12], tabu search [13], simulated annealing [14], [15], neural networks [16] and also the PSO [17] and some variants [18], [19]. In this sense, to solve the problem of portfolios, it was decided to use an AI technique in the optimization process.

III. Mathematical Formulation

Equation (1) formalizes the addressed problem, which has the objective of maximizing the profit of selling energy in multiple markets, including the possibility to buy as well. d represents the weekday, $Nday$ represent the number of days, p represents the negotiation period, $Nper$ represent the number of negotiation periods, $Asell_M$ and $Abuy_S$ are boolean variables, indicating if this player can enter negotiations in each market type, M represents the referred market, $NumM$ represents the number of markets, S represents a session of the balancing market, and $NumS$ is the number of sessions.

$$\begin{aligned}&(Spow_{M \ldots NumS}, Bpow_{S1 \ldots NumS})\\ &= argmax \left[\begin{array}{c} \sum_{M=M1}^{NumM} \left(Spow_{M,d,p} \times ps_{M,d,p} \times Asell_M \right) - \\ \sum_{S=S1}^{NumS} \left(Bpow_S \times ps_{S,d,p} \times Abuy_S \right) \end{array} \right] \quad (1)\\ &\forall d \in Nday, \forall p \in Nper, Asell_M \in \{0,1\}, Abuy \in \{0,1\}\end{aligned}$$

Variables $ps_{M,d,p}$ and $ps_{S,d,p}$ represent the expected (forecasted) prices of selling and buying electricity in each session of each market type, in each period of each day. The outputs are $Spow_M$ representing the amount of power to sell in market M, and $Bpow_S$ representing the amount of power to buy in session S. The equation (2) is expressed the way in which the negotiation prices are obtained. As you can see we have sale prices $ps_{M,d,p}$ and purchase prices $ps_{S,d,p}$.

$$\begin{aligned} ps_{M,d,p} &= Value(d, p, Spow_M, M) \\ ps_{S,d,p} &= Value(d, p, Bpow_S, S) \end{aligned} \quad (2)$$

The $Value$ is obtained by equation (3), and is calculated from the application of the clustering and fuzzy approach.

$$\begin{aligned} &Value(day, per, Pow, Market) \\ &= Data(fuzzy(pow), day, per, Market) \end{aligned} \quad (3)$$

With the implementation of this technique, it is possible to obtain market prices based on the traded volume. For this in obtaining the prices are considered the expected production of a market player for each period of each day. Results can be observed in [20]. Equation (3) defines this condition, where $Value$ represents the price that will be obtained considering the negotiated amount, since this quantity can influence the price, $Data$ refers to the historical data that correlates the amount of transacted power, the day, period of the day and the particular market session.

In (4) is represented the main constrain of this problem. The constrain impose that the total power that can con be sold in the set of all markets is never higher than the total expect production (TEP) of the player, plus the total purchased power.

$$\sum_{M=M1}^{NumM} Spow_M \leq TEP + \sum_{S=S1}^{NumS} Bpow_S \quad (4)$$

There are other constraints that can be applied to the problem, which depend on the nature of the problem itself, e.g. itself, e.g. type of each market, negotiation amount, type of generation of the supported player.

IV. EVOLUTIONARY PSO

Particle Swarm Optimization (PSO), is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling, the main concept of algorithm is information shared and collaboration between individuals (solutions set that involved in the alternative space – particles) across by simulation of social behavior [21].

The EPSO joins together the characteristics of Evolutionary Algorithms and of Particle Swarm Algorithms. The EPSO brings together the best of two paradigms; it is an optimization algorithm using a particle swarm, by it includes information exchanges between particles, during the moves in the search space. It is also an evolutionary computational method, because the solutions characteristics are mutated and transmitted to the next generations, across a selection mechanism [7].

In each iteration, considering a set of individuals, or particles, the swarm evolves during a given number of generations, According to the following general scheme:

A. Replication

Each particle *i* is replicated *r* times, resulting in a total of *r* + 1 particles in the search space.

B. Mutation

Each replica suffers mutation in strategic parameters *w*, by the following equation:

$$w_{ik}^{*} = w_{ik} + \tau N(0,1) \tag{5}$$

where, τ is the learning parameter, previously fixed, and $N(0,1)$ is a number with gaussian distribution with mean 0 and variance 1. The index k (k = 0, 1 and 2), reference to the inertia weight, memory, cooperation and optimal division. This weight w in algorithm start take uniform random values between 0 and 1.

C. Reproduction

Each particle generates one descendant according to the equation of movement, similar to the equation of the standard PSO algorithm:

$$Gbest_i^{k^*} = Gbest_i^k + \tau' N(0,1) \tag{6}$$

$$v_i^{k+1} = w_{i0}^{*}.\, v_i^k + w_{i1}^{*}.\left(Pbest_i^k - x_i^k\right) + w_{i2}^{*}.\left(Gbest_i^{k^*} - x_i^k\right) \tag{7}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{8}$$

Similarly to the PSO, there is one vector that saves the best position of each particle $Pbest_i^k$, and another that saves the best position until the moment found by the swarm, $Gbest_i^k$. However, the latter receives a different treatment. A mutation is applied in order to control the "size" of a diffuse zone around the optimal current found by the swarm, resulting in the vector $Gbest_i^{k^*}$. With this procedure, the auto-adaptive process can focus more or less the orientation of a swarm and allows it to remain "agitated" even when the particles have all converged to the same region of space and are very close to each other [22].

D. Evaluation

Each descendant has its own adaptation available, according to the position that occupies in space.

E. Selection

The selection process is executed by stochastic tournament, the, the best particle in each group of *r* +1 descendant of each individual of previous generations, is selected with probability (1-luck), to constitute a new generation. In other words, the descendant of original particle enters competition with the descendants of the replicate particles. The luck parameter is usually a very small number [22].

V. CASE STUDY

This section presents the case study, and considers the experimentation of the proposed EPSO approach. Results are compared to those achieved with a deterministic method, and with the standard PSO. All approaches have been implemented in MatLab software (version – R2016a), on a computer compatible with 1 processor Intel® w3565 3.2GHz, with 4 Cores, 8 GB of RAM and operating system Windows 10 64bites.

The case study considers five different markets types: the day-ahead spot market, the balancing market, which considers two different sessions, negotiation by means of bilateral contacts, and a local market, at the SG level. In order to create a realistic scenario, some rules are imposed. When participating in the day-ahead spot market, the supported seller player can only sell, on the other hand, in all other market types it is possible to purchase and sell. 10 MW is the limit imposed on the possible amount of negotiated in each market. In balancing market, the player can only sell or purchase in each session in each period, contrarily, in bilateral contracts and local markets both sale and purchase are allowed in the same period (assuming negotiations with different players).

The inputs for the portfolio optimization are: the number of days and negotiated periods, the number of different markets and the associated number of negotiated session, the limits for purchase and sales is each market, the expected negotiated price in each session of each market for each period of each day, depending on the negotiated volume, and the amount of total energy producer (TEP) to be allocated by different markets. The real market prices data is achieved by forecasting/estimation methods. In markets where price is unique for all participants, regardless of the negotiated amount, an Artificial Neural Network (ANN) is used [23] which is trained with values extracted by the Iberian electricity market operator (MIBEL) [24]. In the markets where the electricity price is influenced by the negotiated amount (e.g. negotiated by bilateral contacts and local markets), a prices estimation methodology using fuzzy logic is used [20].

VI. RESULTS

This section presents the results obtained by the proposed methodology applied to the case study. In this case both EPSO and PSO metaheuristics were executed 1000 times so that it is possible to compare results. TABLE I presents the objective function results achieved by the EPSO, PSO and exact deterministic method.

TABLE I. OBJECTIVE FUNCTION RESULTS (€)

Objective function	Deterministic	PSO	EPSO
Minimum	-	571.4824	482.8223
Mean	-	1483.835	1579.3948
Maximum	2000.645575	1998.601	2000.6454
STD	-	270.3166	237.0183

As can be seen from TABLE I the deterministic method only has an objective function value, because as it is an exact resolution, thus it is only executed one time, since it presents no variation. The metaheuristic methods results include the minimum, mean, maximum and standard deviation (STD) values. The measurements result from the 1000 simulation. The maximum values of three methods are very close, the PSO presents the smaller maximum value between three methods, and has a difference of 2.04 from deterministic resolution, while the EPSO achieves a higher maximum value with a difference of 1.75×10^{-4} when compared to deterministic resolution. In terms of STD it can also be observed that the value is better since it is lower, and in this case the smaller STD the better, since it represents a smaller variation of results in 1000 simulation for PSO and EPSO resolutions. TABLE II presents the results for execution time and number of required iterations.

TABLE II. TIME AND ITERATIONS RESULTS

Methods	Time		Iterations	
	Mean	STD	Mean	STD
Deterministic	247244.1882		-	-
PSO	0.1836	0.0353	64	10.91
EPSO	27.93	54.81	1620.58	3173.91

As it can be seen in TABLE II, the deterministic resolution only has value for the execution time, and here is the great advantage of the use of the metaheuristics because as it can be observed, the metaheuristics take in mean 1% of the time to obtain a solution compared to the deterministic resolution.

Figure 1 shows the scheduling of sales in different markets, comparing the results achieved from EPSO and standard PSO resolutions. As can be observed, the solutions have small differences. In the Spot market, EPSO has a higher allocated value, in SG and bilateral contracts, the PSO has a higher amount of sales. Figure 2 shows the allocated amounts of purchase in the different markets.

As can observed in Figure 2, both methods have allocated the purchase of the maximum allowed amount in the balancing markets. In bilateral contracts, EPSO allocates more electricity amount then PSO for purchase. As can be observed, since the spot market has been used to sell electricity, it cannot be used to purchase as well, according to the restriction defined in the model. In the case of balancing markets sessions, it assumes values 0 for sales, because these markets are used to purchase electricity due to the lower expected prices. In Figure 3 is present the variation of price for the different considered markets, according the amount of negotiated electricity.

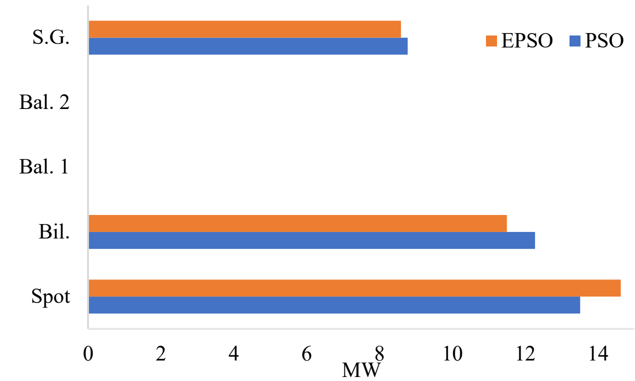

Figure 1. Amount of sales in the different markets

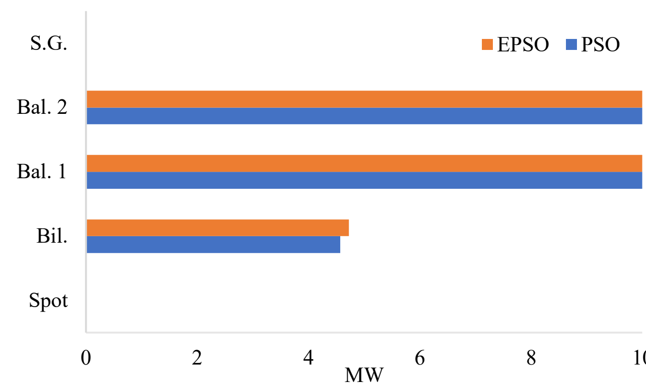

Figure 2. Amount of purchase in the different markets

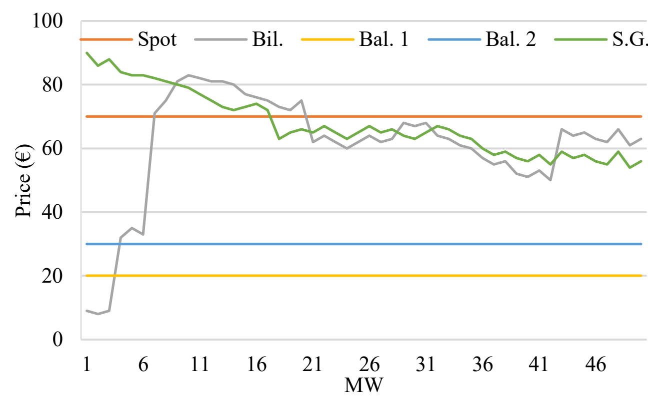

Figure 3. Price variation

From Figure 3 it can be observed that the expected prices in the day-ahead market and in the different sessions of the balancing market are constant regardless of the negotiated amount, in bilateral contracts negotiation and in SG negotiations, it is visible that the expected price is not linear, it varies depending on the negotiated amount. With the proposed model, it is possible to purchase certain quantities of electricity when the price is lower and sell it in opportunities when the expected price is higher, in order to obtain the maximum possible profit.

By matching Figure 3 with Figure 1 and Figure 2 it is possible to understand the functioning of the model. As expected, the model presents a solution with the purchased electricity in the cheapest markets and sales in the most profitable. As the total energy that can be bought in each market is 10 MW, the maximum amount is bought in the balancing sessions (lower prices), and a purchase of 4.7 MW in bilateral contracts – an amount for which there is a peak of low expected price. The sale is set to the SG in 8.6 MW, 12.3 MW in bilateral contracts and 13.8 MW in the spot market.

VII. CONCLUSION

This paper presented a methodology based on EPSO to optimize the scheduling of electricity negotiations in multiple market opportunities. The resolution of this problem using the EPSO method is compared to the performance of an exact method and of the classical PSO metaheuristic.

As results show, both the PSO and the EPSO presented very close results to the deterministic resolution in terms of objective function values. Regarding the execution time, the PSO and EPSO proved to be much faster, which gives them a great advantage in relation to the deterministic resolution, but EPSO reaches a higher maximum than the PSO and a lower STD; thus EPSO is more reliable and enables reaching higher objective function values. In support of the decision of the EM it is necessary to have answers in short intervals of time in order to enable coping with fast and multiple negotiation processes. Therefore the resolution by metaheuristics becomes favorable. From the achieved results it is possible to verify that the model complied with all the rules imposed. The comparison between PSO and EPSO can be made by observing the value of the objective function where the EPSO presented a better maximum and mean value, with a smaller STD. However, the EPSO takes longer than the PSO to execute, but when compared to the deterministic resolution this value is residual. In [12], the same case study is carried out using GA. Results using GA present differences with regard to EPSO, namely the maximum value of the 1000 simulations, in which EPSO is able to achieve higher values.

As future work, this methodology will be associated with a risk measure, so that it becomes possible for the user to choose the desired level of risk for the allocation of negotiation power, thus balancing the expected profit with the risk exposure.

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