Multi-Agent Electricity Market Simulation with Dynamic Strategies & Virtual Power Producers

Isabel Praça, Hugo Morais, Carlos Ramos, Member, IEEE,
Zita Vale, Member, IEEE, Hussein Khodr, Member, IEEE

Abstract -- Distributed energy resources will provide a significant amount of the electricity generation and will be a normal profitable business. In the new decentralized grid, customers will be among the many decentralized players and may even help to co-produce the required energy services such as demand-side management and load shedding. So, they will gain the opportunity to be more active market players. The aggregation of DG plants gives place to a new concept: the Virtual Power Producer (VPP). VPPs can reinforce the importance of these generation technologies making them valuable in electricity markets. In this paper we propose the improvement of MASCEM, a multi-agent simulation tool to study negotiations in electricity spot markets based on different market mechanisms and behavior strategies, in order to take account of decentralized players such as VPP.

Index Terms – Sustainable Development, Decision-making, Distributed Generation, Electricity Markets, Intelligent Agents Coalitions, Virtual Power Producers

I. NOMENCLATURE

DG – Distributed Generation
MASCEM – Multi-Agent Simulator of Competitive Electricity Market
VPP – Virtual Power Producer

II. INTRODUCTION

In competitive electrical energy markets, market players have to operate with well supported strategic behavior in order to attain their goals. These markets are relatively recent and exhibit significantly different characteristics from other commodities markets. Due to this, electricity market players lack experience in market participation.

The success of electricity markets relies not only on adequate regulation models and on efficient and fair market and system management, but also on market participants’ success. In the context of competitive markets, market players experience a high risky business which consequences can be suffered by the power sector. Derivatives markets allow mitigating the risks but can only mean a significant improvement if adequately used by market players.

The success of each player participation in the market can be determined by the use of adequate decision-support tools. These tools should be seen as part of a complete electricity market simulation tool.

Competitive electricity markets are dynamic complex environments in which a lot of different kinds of players play a diversity of roles. These players have to take decisions which impact can be enormous both for individual players but also for the whole market. To adequately simulating such an environment, multi-agent systems show an important set of advantages.

Agents are autonomous or semi-autonomous entities that can perform tasks in complex and dynamically changing environments. Agent technology seems to be an appropriate paradigm for use in modeling individual participants of electricity markets since they exhibit some relevant capabilities like autonomy, adaptability and ability to interact with others.

A Multi-Agent System consists of a group of agents that combine their specific competencies and cooperate in order to achieve a common goal. Efficient cooperation as well as coordination procedures between agents endows a Multi-Agent System with a capability higher than the sum of the individual agent capabilities.

Agents and multi-agent systems that adequately simulate electricity markets behavior are essential tools to gather knowledge and provide market agents with decision-support to strategic behavior. A wide variety of existing tools and services are available concerning agent-base research on restructured electricity markets [15].

This paper discusses the use of agent-based simulation for the study of electricity markets at the wholesale level, and explores distributed generation by including Virtual Power Producers on the Model.

MASCEM – Multi-Agent Simulator of Competitive Electricity Markets [13] was developed to study several negotiation mechanisms usually found in electricity markets. In MASCEM market participants have strategic behavior and a scenario decision algorithm to support their decisions.

MASCEM provides users with dynamic strategies which
can be specifically tailored to adapt themselves to each agent characteristics and to each situation. Moreover, MASCEM provides decision-support tools that can be accessed by each agent for simulation purposes.

This paper focus on the negotiation strategies supported by MASCEM, providing the means to take conclusions about the relevance of the existence of dynamic strategies and decision-support tools to support market players’ behavior.

The paper also addresses the inclusion of Virtual Power Producers (VPP) models and simulation tools in the scope of MASCEM. VPPs represent the aggregation of a set of producers, mainly based on distributed generation (DG) and renewable sources. They can provide the means to adequately support DG increasing use and its participation in the context of competitive electricity markets.

Section III provides a general overview of MASCEM. Section IV focus on VPP agents and presents some results concerning producers’ remuneration.

Finally, Section V presents the most relevant conclusions.

III. MASCEM OVERVIEW

One of the main objectives of electricity markets is to decrease electricity costs through competition. Several market structure models exist that could help achieve this goal. The market environment typically consists of a Pool, as well as a floor for Bilateral Contracts [16].

A Pool is a marketplace where electricity-generating companies submit production bids and their corresponding market prices, and consumer companies submit consumption bids. A Market Operator regulates the pool. The Market Operator uses a market-clearing tool to set market price and a set of accepted production and consumption bids for every hour. In Pools, an appropriate market-clearing tool is an auction mechanism. Bilateral Contracts are negotiable agreements between two traders about power delivery and receipt. The Bilateral-Contract model is flexible; negotiating parties can specify their own contract terms. The Hybrid model combines features of Pools and Bilateral Contracts. In this model, a Pool is not mandatory, and customers can either negotiate a power supply agreement directly with suppliers or accept power at the established market price. This model therefore offers customer choice.

To gain insights into decentralized electricity markets, we developed MASCEM, a Multi-Agent Simulator that implements the referred negotiation mechanisms. Unlike traditional tools, MASCEM does not postulate a single decision maker with a single objective for the entire system. Rather, agents, representing the different independent entities in Electricity Markets, are allowed to establish their own objectives and decision rules. Moreover, as the simulation progresses, agents can adapt their strategies, based on the success or failure of previous efforts. Learning capabilities enable market agents to update their knowledge, according to their own past behavior and with other agents’ behavior. In each situation, agents dynamically adapt their strategies, according to the present context and using the dynamically updated detailed knowledge.

1. MASCEM Multi-Agent Model

There are several entities involved in the negotiations; we propose a multi-agent model to represent all the involved entities and their relationships. Figure 1 illustrates the Multi-Agent Model.

MASCEM multi-agent model includes: a Market Facilitator Agent, Seller Agents, Buyer Agents, a Market Operator Agent and a System Operator Agent. Three types of markets are simulated: Pool Markets, Bilateral Contracts and Hybrid Markets.

Fig. 1. MASCEM negotiation framework

The Market Facilitator is the coordinator of the market. It knows the identities of all the agents present in the market, regulates the negotiation process and assures the market is functioning according to the established rules. The first step agents’ have to do to participate in the market is to register at the Market Facilitator, specifying their market role and services.

Seller and Buyer Agents are the two key players in the market. Sellers represent entities able to sell electricity in the market, e.g. companies holding electricity production units. Buyers may represent electricity consumers or even distribution companies. The user, who must also specify their intrinsic and strategic characteristics, defines the number of Sellers and Buyers in each scenario.

Sellers will compete with each other, since each seller is
interested in maximizing its profits. On the other hand, Sellers will cooperate with Buyers while trying to establish some agreement that is profitable for both. From this point of view, electricity markets are a very rich domain where it is possible to develop and test several algorithms and negotiation mechanisms for both cooperation and competition.

The System Operator Agent represents the responsible for the transmission grid and all the involved technical constraints. Every established contract, either through Bilateral Contracts or through the Pool, must first be communicated to the System Operator, who analyses its technical feasibility from the Power System point of view (e.g. analyzing line power flows).

The Market Operator Agent represents the responsible for the Pool mechanism. This agent is only present in simulations of Pool or Hybrid markets. The Market Operator will receive bids from Sellers and Buyers, analyze them and determine the market clearing price (MCP) and accepted bids.

MASCEM facilitates agent meeting and matching, besides supporting the negotiation model. In order to have results and feedback to improve the negotiation models and consequently the behavior of user agents, it simulates a series of negotiation periods, \( D = \{1, 2, \ldots, n\} \), where each one is composed by a fixed interval of time \( T = \{0, 1, \ldots, m\} \). When simulating a Pool or Hybrid market, in each day, these periods correspond to the 24 one hour periods (or, alternatively, to 48 half-hour periods).

Moreover, each agent defines periods which are important for analyzing its results and for defining the strategic behavior to apply in the following period(s). Although this is not a constraint imposed by the simulator, in the case of electricity market simulation, these periods are always longer than the day-ahead market negotiation periods. They tend to correspond to one full day when defining strategies to operate in the Pool and to much longer periods when defining strategies to negotiate Bilateral Contracts. These periods are called strategic-periods (or S-periods) in the context of MASCEM, as they are defined by each agent according to its strategic needs.

At a particular S-period, each agent has an objective that specifies its intention to buy or sell and on what conditions. These conditions are then detailed to each negotiation period.

The available agents can establish their own objectives and decision rules. Moreover, they can adapt their strategies as the simulation progresses, on the basis of previous efforts success or failures. The simulator probes the conditions and the effects of market rules, by simulating the participants' strategic behavior.

2. MASCEM Negotiation

On the basis of the results obtained in a period, Sellers and Buyers revise their strategies for the next S-period. Seller and Buyer Agents have strategic behavior to define their desired price. These agents have time-dependent strategies, and behavior-dependent strategies, to define the price in the following periods next period according to the results obtained in the previous ones.

MASCEM implements four basic types of strategies to change the price during a defined S-period: Determined, Anxious, Moderate and Gluttonous. The difference between these strategies is the time instant at which the agent starts to modify the price and the amount it changes. Although time-dependent strategies are simple to understand and implement [10], they are very important since they allow the simulation of important issues such as: emotional aspects and different risk behaviors. For example, an agent using a Determined Strategy is a risk indifferent one. On the contrary, Gluttonous agents exhibit less risk aversion than agents using Anxious and Moderate Strategies, since they keep the price constant for a long time, taking the risk of not selling. Based on each agent goals and knowledge, alternative strategies are composed.

To adjust price between S-periods, also referred as behavior-dependent strategies, MASCEM provides two basic strategies: one called Composed Goal Directed and another called Adapted Derivative Following. These are important strategies that use the knowledge obtained with past experiences to define bid prices for next periods.

The Composed Goal Directed strategy is based on two consecutive objectives, the first one is selling (or buying) all the available capacity (power needed) and then increase the profit (reduce the payoff).

The Adapted Derivative Following strategy is based on a Derivative Following strategy proposed by Greenwald [6]. The Adapted Derivative-Following strategy adjusts its price by looking to the amount of revenue earned in the previous S-period as a result of the previous period’s price change. If the last period’s price change produced more revenue per good than the previous period, then the strategy makes a similar change in price. If the previous change produced less revenue per good, then the strategy makes a different price change.

The price adjustment is based on the same calculation for both strategies and takes into account the difference between the desired results and the obtained results in the previous period (details and case-study in [14]).

In general, using a very simplified approach, one can say that the only goal of the player that participate in a market is to maximize its profits or minimize its costs. However, this does not correspond to the reality when there are more factors to consider than the economic ones or when these must be considered over relatively long periods of time.

In the case of electricity markets, buyers, when representing electricity consumers or consumer aggregations, although aiming at minimizing their costs, can have as primary goal to acquire all the required amount of electrical energy. In this case, the Composed Goal Directed strategy is more adapted to their objectives.

On the contrary, sellers, representing directly a producer or an aggregation of producers, have profit maximization as the primary goal. Although this can seem very clear, there are some intrinsic factors that can make this problem more complex. For instance, profits must take into account no only
the amount of produced energy but also the conditions of this production. According to the used production technology, it may be better to produce less in certain periods to attain better results in alternative periods. Moreover, penalties, which are applied in some market models, must also be considered.

According to each player model and knowledge, these strategies are composed with more specific strategies, giving place to specially tailored strategies for each agent. As an example, in the case of producers, the specific strategies take into account the production technology. In the case of production technologies based on renewable sources, highly dependant from weather factors, these are considered. For each player, all relevant strategies are composed, according to the player defined goals and to the identified situation. In this way, player strategic behavior depends from several aspects, namely the following:

- player defined goals;
- player model (including technical characteristics);
- player knowledge (namely concerning other players’ models);
- context (taking into account factors of different nature, including market regulation, external factors such as oil prices, weather, which is considered in the player model but also in a more general context, namely for load forecasting, …).

This approach makes players’ strategies adaptive both to each player and to each situation.

3. Scenario Analysis Algorithm

To obtain an efficient decision support, Seller and Buyer agents should have the capability of using a Scenario Analysis Algorithm. If one hopes to get simulation results which are close to reality, the simulator must consider players with different decision support tools. Each player can be represented as having access to a set of tools, which are used to support its decisions.

In this paper, we will consider that some players have access to a scenario analysis algorithm able to support strategic behavior. We have developed this particular algorithm with the aim of providing complex support to develop and implement dynamic pricing strategies. Each agent analyzes and develops a strategic bid, taking into account not only its previous results but also other players results and expected future reactions. This is particularly suitable for markets based on a Pool or for Hybrid markets, to support Sellers and Buyers decisions for proposing bids to the Pool and accepting or not a bilateral agreement. This algorithm uses data mining and game theory; its organization is presented in Figure 2.

The algorithm is based on analyzing several bids under different scenarios, constructing a matrix with the obtained results and applying a decision method to select the bid to propose. Each agent has historical information about market behavior and about other agents’ characteristics and behavior.

To get warrantable data, each agent uses techniques based on statistical analysis and knowledge discovery tools, which analyze the historical data. With the gathered information, agents can build a profile of other agents including information about their expected proposed prices, limit prices, and capacities. With these profiles, and based on the agent own objectives, several scenarios, and the possible advantageous bids for each one, are defined.

The agent should analyze the incomes that result from bidding its limit, desired prices, and competitive prices—those that are just slightly lower (or higher, in the Buyer’s case) than its competitors’ prices.

A pair bid-scenario is referred as a play. After defining all the scenarios and bids, market simulation is applied to build a matrix with the expected results for each play.

The matrix analysis with the simulated plays’ results is inspired by the game theory concepts for a pure-strategy two-player game, assuming each player seeks to minimize the maximum possible loss or maximize the minimum possible gain [4].

A Seller—like an offensive player—will try to maximize the minimum possible gain by using the MaxiMin decision method. A Buyer—like a defensive player—will select the strategy with the smallest maximum payoff by using the MiniMax decision method.

Buyers’ matrix analyses leads to the selection of only those situations in which all the consumption needs are fulfilled. This avoids situations in which agents have reduced payoff but cannot satisfy their consumption needs completely.

The analysis of each period’s results will update the agent’s market knowledge and the scenarios to study. After each period, instead of considering how they might increase, decrease, or maintain their bid, agents use knowledge rules that restrict modifications on the basis of other agents’ expected behavior. The knowledge rules update agents’ bids in each scenario, but the number of scenarios remains the
same. If at the end of a negotiation period the agent concludes (by analyzing market results) that it incorrectly evaluated other agents’ behavior, it will fix other agents’ profiles on the basis of the calculated deviation from real results.

Several experiences were made to evaluate the benefits of the Scenario Analysis Algorithm (SAA). In this section we describe a small and simple scenario to illustrate them. The scenario used is very simple to let the reader better understand it. Table I presents Seller agent intrinsic characteristics and Table II those for Buyer Agents.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>SELLER AGENTS</th>
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<tbody>
<tr>
<td></td>
<td>Limit Price</td>
</tr>
<tr>
<td></td>
<td>Cent/kWh</td>
</tr>
<tr>
<td>S1</td>
<td>1.56</td>
</tr>
<tr>
<td>S2</td>
<td>2.86</td>
</tr>
<tr>
<td>S3</td>
<td>3.15</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>BUYER AGENTS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Limit Price</td>
</tr>
<tr>
<td>B1</td>
<td>3.67</td>
</tr>
<tr>
<td>B2</td>
<td>3.30</td>
</tr>
</tbody>
</table>

Seller S1 is the most competitive one, having prices smaller than the other agents. This agent may increase its profits by raising its pretended price, without being overcome by competitors. The agent can use the SAA to take this conclusion. Let’s see what happens in the Asymmetric Pool and in the Symmetric Pool.

**Asymmetric Market**

In this type of market only Sellers are able to compete by presenting bids to the Pool. The Pool mechanism is usually the First Price Sealed Bid Auction. According to this mechanism, market price will be established based only on Seller bids and previewed demand. So, agents will consider only profiles of other Seller agents.

Agent S1 may use SAA to build a profile of other agents and test bids that approach their expected bids but are sufficiently smaller to overcome them. Table III shows S1 profit fluctuation when compared to the same scenario simulated without the use of SAA.

<table>
<thead>
<tr>
<th>TABLE III</th>
<th>SELLER S1 PROFITS IN ASYMMETRIC MARKET</th>
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<tbody>
<tr>
<td></td>
<td>S1 Profit Fluctuation</td>
</tr>
<tr>
<td>Only S1 uses SAA</td>
<td>25 %</td>
</tr>
<tr>
<td>All Sellers use SAA</td>
<td>3 %</td>
</tr>
<tr>
<td>All Sellers except S1 use SAA</td>
<td>- 6 %</td>
</tr>
</tbody>
</table>

As we can see the major profit increase happens when S1 is the only agent using SAA. That makes sense since the other agents, which are less competitive, are not using SAA to conclude it and so they will keep trying to obtain their desired prices instead of making smaller bids, like those based on their limit prices. When the other Sellers also use SAA they conclude they cannot overcome S1, but they may compete with each other and so they reduce their pretended prices. In periods where S1 is not able to satisfy all consumption needs, such as in peak periods, the market price will be established by S2 or S3. Since they decrease their bids, market price will also be decreased, and so S1 profits will, indirectly, be reduced.

**Symmetric Market**

In Symmetric Markets, the Pool functions according to a Double Uniform Auction, so both Sellers and Buyers are able to compete by presenting bids to the Pool.

When using SAA agents will also analyse bids that approach Buyers proposals that means that when studying Symmetric Markets the number of plays to analysed is higher.

As we can see in Figure 3, since Buyer Agents pretended prices are smaller than those presented by Sellers, the S1 Agent will conclude he is not able to increase bids as much as in the Asymmetric Market.

![Fig. 3. Symmetric Market Mechanism](image)

Table IV shows S1 profit fluctuation when compared to the same scenario simulated without the use of SAA.

<table>
<thead>
<tr>
<th>TABLE IV</th>
<th>SELLER S1 PROFITS IN SYMMETRIC MARKET</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S1 Profit Fluctuation</td>
</tr>
<tr>
<td>Only S1 uses SAA</td>
<td>12 %</td>
</tr>
<tr>
<td>All Sellers use SAA</td>
<td>-5 %</td>
</tr>
<tr>
<td>All Sellers except S1 use SAA</td>
<td>- 13 %</td>
</tr>
</tbody>
</table>

As expected S1 profits are smaller than the obtained in the Asymmetric Market. On one hand, according to the Pool mechanism, Buyer Agents are able to submit bids, so they are also able to influence market price. On the other hand, since Buyers pretended prices are smaller than Sellers prices, S1 concludes, trough the SAA, that he can not raise its price, as much as in the Asymmetric Market, since in that market only Seller profiles are considered[10].
IV. VIRTUAL POWER PRODUCERS AGENTS

Virtual Power Producers (VPPs) are multi-technology and multi-site heterogeneous entities, being relationships among aggregated producers and among VPPs and the remaining Electricity Market agents a key factor for their success.

To sell energy in the market VPP must forecast the generation of aggregated producers and “save” some power capacity to assure a reserve to compensate a generation oscillation of producers with natural resources technologies dependent.

The VPP can use different market strategies in S-period, considering specific aspects such as producers established contracts and range of generation forecast. The prediction errors increase with the distance between the forecasting and the forecast times. The standard error figures are given as percent of the mean production, since this is what the utilities are most interested in (installed capacity is easy to measure); sometimes they are given as percent of the mean production or in absolute numbers.

Considering an example of Spanish market (OMEL), the spot market session closes at 11:00 AM, therefore the time slice between the predictions and real day is 13 to 37 hours [2-12]. In this context, the VPP can change its market strategy during the day to manage the risk. These strategies are also depending of reserves, in other words, VPP can change the reserve to maintain the risk, however, if VPP has a bigger reserve the costs is higher.

Another important factor to the VPP market strategy is the buy energy price to the aggregated producers [3-9]. The price considered for each producer must be agreed with the VPP so that competitive prices can be obtained, to allow the producers to have revenues from their investments in reasonable periods of time.

If subsidies exist, these will have to be included in the calculation of the prices considered for the producers. The price of the reserve will also have to be previously agreed between the VPP and the producers.

This way of working implies a great complicity between the VPP and the associated producers in order to prevent speculations. The profit edge is variable, but the minimum value is given by the value of sell percentage.

In markets where price variations are frequent, the VPP will be able to define different strategies, as for example, the prices elaboration depending on the generating technologies, to obtain prices that can be easily adapted to the market.

In this scenario the technologies can be divided in 4 groups. The first group will include the technologies for which the primary energy cannot be stored, as for example wind, solar, and co-generation.

The second group includes the technologies for which it is possible to store the primary resource and for strategically interests it could be convenient to use the resources in the periods when the price of energy is higher. The technologies that belong to this group are the hydroelectric with dam, the biomass and biogas.

The third group includes the VPP reserve, either the production part that the VPP has contracted for reserve with the producers or with thermal central offices.

The fourth group includes the technologies for which the primary resources are storable, but expensive, as for example, gas turbines and fuel cells.

For the first group, whatever is the final price, it is always better than to waste the existing resources, therefore the VPP will have to adjust its strategy to obtain the best final sell price, but having in mind that even when the price is low, it may be interesting for the producers.

For the second group the way of using the resources must be managed with care to valuing them as most as possible. However, if the resources are in excess and it is not possible to store them, these could be used in periods in which the prices are lower. In these situations, the VPP will have to consider these producers in the same way it considers those in group 1.

For the third group the VPP will have to consider the difference between the price to be paid for the produced energy and the price to be paid for the reserve.

In the fourth group, the considered price will be constant during the day. The factor that could be changeable is the amortization of the investment; it should consider at least the marginal cost.

In the countries where subsidies exist, the VPP will be able to obtain very competitive prices what makes its participation in the market easier.

A model has been developed to simulate the operation of a VPP, taking into account the characteristics of the technologies used by the power producers and can be used to provide decision support to VPPs.

With MASCEM simulation tool, several studies were done, using different levels of reserve. The goal was to verify which is the most advantageous strategy to pay the energy to the producers. On the other hand, this tool will be very useful for the producers because it can verify, in different conditions, how much it receives when aggregated to the VPP [7-8].
The figures 4 and 5 present some results of study of producers remuneration by VPP, considering wind farm and co-generation technologies.

These results show the advantages that each producers has when aggregated to the VPP in what concerns its remuneration. In general, when the produced energy is lower than forecasted, this advantage can be traduced in higher profits. On the contrary, when the produced energy is higher that the forecasted, producer remuneration can be lower when associated with a VPP. In what concerns remuneration values, wind generation is the one that most benefits from the aggregation. However, there other significant advantages besides remuneration, namely the providing by the VPP of relevant services (market bidding, maintenance, ...). These are especially important for other production technologies with smaller size.

V. CONCLUSION AND FURTHER WORK

This paper presented MASCEM, a multi-agent electricity market simulator. This simulator allows to study electricity markets and to provide market players with adequate support. Each market participant has its own business objectives, and decision model. The results of the negotiations between agents are used by agents in order to extract knowledge that gives feedback to improve their strategies. The extracted knowledge will be used to set up probable scenarios, analyzed by means of simulation and game theory decision criteria.

The paper presented the dynamic strategy infrastructure provided by MASCEM, which supports the elaboration of complex composed strategies, specifically tailored to each market participant and to each situation. A small example illustrates the conclusions of the undertaken simulation studies which show the significant contribution of these strategies to increase players’ goals accomplishment.

MASCEM supports Virtual Power Producers (VPP) models and simulation and decision-support decision tools specifically developed for this kind of agents. The paper includes some examples concerning the simulation of VPP participation in the market. The remuneration of the producers is in fact a complex issue of VPP operation, since there are opposite interests in game, however, Viprod obtain good results of producers remuneration.
VI. REFERENCES


VII. BIOGRAPHIES

Isabel Praça graduated in the University of Porto in 1994 and received her Ph.D degree in Electrical Engineering from the University of Trás-os-Montes e Alto Douro in 2005. She is currently a Professor in the Polytechnic Institute of Porto. Her research areas include Multi-Agent Systems, Simulation, Decision Support Systems and Electricity Markets.

Hugo Morais received the B.Sc. degree in 2005 from the Polytechnic Institute of Porto, Porto, Portugal. He is also a PhD student with the University of Trás-os-Montes e Alto Douro, Vila Real, Portugal and his research interests include distributed generation and future power systems.

Zita A. Vale is a Coordinator Professor of Power Systems at the Engineering Institute – Polytechnic Institute of Porto (ISEP/IPP), Portugal. She received her diploma in Electrical Engineering in 1986 and her PhD in 1993, both from University of Porto. Her main research interests concern Artificial Intelligence (A.I.) applications to Power System operation and control, Electricity Markets and Distributed Generation. She is involved in several R&D projects concerning the application of A.I. and Decision-Support techniques to Engineering problems.

Carlos Ramos received his graduation (1986) and his PhD (1993) in Electrical Engineering from the University of Porto. He is Coordinator Professor of Computer Engineering at the Polytechnic Institute of Porto/Institute of Engineering. His main R&D interests are Artificial Intelligence and Decision Support Systems.

H. M. Khodr (M’99) received the Ph.D. and M.Sc./Engineer degrees in Electrical Engineering from the José Antonio Echeverría Higher Polytechnic Institute (ISPIAE) in 1997 and 1993 respectively. Former Associate Professor of Electrical Engineering at Simón Bolívar University, Venezuela. He was a Researcher at INESC porto, Portugal. Presently, he is a Researcher at GECAD – Knowledge Engineering and Decision-Support Research Group of the Electrical Engineering Institute of Porto – Polytechnic Institute of Porto (ISEP/IPP). He has participated in a number of projects performed for the local industries. His current research activities are concentrated on planning, operation, and economics of electrical distribution and industrial power systems, power quality, grounding systems and optimization.