International Congress on Evolutionary Methods for Design,
Optimization and Control with Applications to Industrial Problems
EUROGEN 2003
G. Bugeda, J.A.- Désidéri, J. Periaux, M. Schoenauer and G. Winter (Eds)

APPLICATION OF AN OPTIMIZING SUPPLY STRATEGIES MODEL IN THE SPANISH ELECTRICAL MARKET

Enrique A. de la Cal Marín[†] and María del Rosario Suárez Fernández[*]

[†]Metrology and Models Laboratory, Computer Science Department
University of Oviedo, Viesques Campus, 33203 Gijón, Spain
Email: delacal@ccia.uniovi.es

[*]Metrology and Models Laboratory, Computer Science Department
University of Oviedo, Viesques Campus, 33203 Gijón, Spain
Email: mrsuarez@correo.uniovi.es

Key words: Coevolutive Genetic Algorithm, Fuzzy Classification, Multi-criterium fitness, Evolutionary Economics.

Abstract.

The price of electrical energy in Spain has not been regulated by the government since 1998, but determined by the supply from the generators in a competitive market, the so-called "electrical pool".

In this work, we present a methodology to improve the profit of the competitive firms and detect collaboration situations in the pool.

This methodology is based on genetic algorithm-based method that allow us to simulate the behavior of the Electrical Spanish strategies agents when hard deviations are applied on one agent strategy. A perfect oligopolistic behavior of the agents will be assumed.

1 Introduction

The relationship between the cost of production and the selling price of electrical energy is not direct. Production cost determines price in a regulated market, such as the one that existed in Spain before 1998 and continues to exist in other European Community countries. This is not so in a competitive market. Before 1998, prices in Spain were fixed by a public agency that was also in charge of elaborating a list of the power plants that should connect at any given time. This list was calculated by means of numeric optimization algorithms, which minimized the global cost of the production necessary to cover domestic demand.

In the modern model, based on free competition among the different companies [2], the Market Operator (MO), a neutral agent appointed by the State to regulate competition, calculates the energy prices for every hour, starting from the supply of the generators and the demand of the consumers, this process is called "casation procedure".

The procedure by which production is planned is based on the principle that "the cheapest power plants connect first". In this case, however, "cheapest" does not mean "low cost", but "low selling price", because each agent is free to choose the price it wants to charge for its power. It is interesting to note that the law stipulates that all power plants are to receive the same payment for each MW of energy sold, as occurred in the non-competitive model, and not the payment they asked for in their strategy. The second principle of the competitive market is "the most costly power plant connected marks the price".

In previous works [4], [3], we designed a genetic tool (Tool_1) able to estimate past offers from the agents in the pool from publicily available data: hourly prices and amount of energy consumed. This last model was a useful analysis tool in certain situations: it allowed us to estimate the change in the price of the electrical energy under small deviations of the supply curves of one agent. The simulation procedure was as follows:

1. The supply curves of all agents are estimated by means of the genetic tool.
2. One of the supplies is slightly modified. For example, the selling price of a group of generators is lowered.
3. A new simulation is carried with the modified supply curve and the original demand. Supply curves of the remaining agents remained untouched. In other words, it was assumed that the agents *did not react to the change*, changing their prices to maintain their market share.

In other work [5], we presented a new tool (Tool_2) to generalize the previous tool by dropping this last assumption. In other words: what would happen if the agents are allowed to react? We confront with a game theory problem, which we solve by means of cooperative-fitness based genetic algorithms.

In present work, we propose a methodology, that use Tool_2, to analyze the influence on a pool when hard deviations are made over a supply curve agent with reaction of the remaining agents supply curves. Also, we shows the numerical results from applying above methodology to a semi-synthetic problem.

1.1 Summary

The remainder of this paper is arranged as follows: The "casation process" in term of Games Theory is described in Section 2. Our methodology and genetic algorithm is described in Section 3. In Section 4, the methodology is applied to a Semi-Synthetic problem. The paper finishes with concluding remarks

2 Electrical pool as a game theory problem

Given that preliminary data are insufficient to carry out a statistical analysis, it is necessary to make conjectures regarding the results. This work assumes that the agents are intelligent and that the market is fair, such that the unit profits (euros/MW) are approximately the same for all the competitors.

With these hypotheses, if we know the cost of production of the agents (and we can estimate that, using data prior to 1998), it is possible to simplify market operation and abstract it to a game, which can be explained as follows. Let us assume that a certain amount of energy is to be bought from several generators. None of them is capable of supplying the total amount and the amount supplied by all of them exceeds the needs.

Each player (one of the generators) gives a referee (the MO) a closed envelope with its sales strategy. It consists of a pair "quantity supplied - price demanded per unit". The referee opens the envelopes, arranges the strategies and chooses the cheapest ones until demand is covered. Each player selected is then paid for the amount it sells at the price of the most expensive strategy that was accepted.

Each player receives the difference between the price paid and their unit cost, multiplied by the energy units sold.

The actual number of players is several hundred (one player per electrical power plant). To simplify calculations, we group the price-quantity pairs of all the power plants belonging to the same company into a single total quantity produced-unit price curve. In this way, we reduce several hundred strategies to four aggregate supply curves (there are four large electrical companies in Spain). The same is done with costs: each of the four participants in the simplified game will have a curve that relates the negotiated MW with their production cost. The mechanism of this new game is a bit more complex: each player gives the referee an aggregate supply curve. The referee adds up all the curves and intersects the results with a demand curve(it depends the price). The cross point determines the market price. Given the price and the supply curves furnished by the agents, the revenue of each player is calculated.

Finally, the net profit of each player is calculated using the difference between the income received and the value of its cost curve at the point corresponding to the amount negotiated.

3 Proposed methodology

In this work, we want to estimate the reaction of the remaining competing agent supply curves when a deviation is applied on one agent strategy curve.

In previous work, we use our tool Tool_1, [4], to estimate the change in the price under "small deviations" of the supply curve of one agent. Then, it was assumed that the "competing agents did not react to the change", changing their prices to maintain their market share. In present work we drop above assumption and we use our optimization tool Tool_2, [5], to simulate the reaction of agents when "hard deviations" are applied on one agent. Tool_2 was used in previous work to calculate optimal supply generation curves of agents competing in the electrical pool. Here, we use Tool_2 to define our methodology steps:

1. The supply curve of all agents are estimated by means of our genetic tool Tool_1.
2. One of the supplies agent is hardly modified. For example, the quantity of energy generated by a group of generators is raised.
3. By the last, Tool_2 is applied to estimate the reactive supply curves of the remaining agents. The modified supply curves agent is kept unchanged.

3.1 Using Tool_2 to simulate reactions to a modified supply curve

Genetic Tool_2 defines a nonlinear parametrization of the supply curves and use a co-evolutionary genetic algorithm to find an equilibrium point generalizing, what is termed Cournot equilibrium [1], Cournot equilibrium to our own definition of supply curve. Briefly, the genetic algorithm works as follows: first, we define as many populations of strategies as players. The population corresponding to modified supply curve agent is initialized with its modified supply curve and is not evolved during simulating. To score a strategy, we will simulate a game, making this strategy to compete with a selection of strategies taken from the remaining players.

The algorithm studied in this work serves us to obtain (in Cournot terms) the reactive supply curves of the companies competing in the market using demand curves of several previous markets and the modified supply curve. The input data are the demand curves, the costs of generation of all competing firms and the modified supply curve. The outputs –the supply curves– represent market strategies.

3.2 Genetic Model

3.2.1 Definition of a supply curve

Strategic Planning Departments take into consideration the day of the week, the hour of the day, the season, the weather forecast (rain, temperature) and some other indicators before posting prices to the Market Operator. Following our own experience, three features should be considered: the hour (which is related to the amount of energy negotiated,

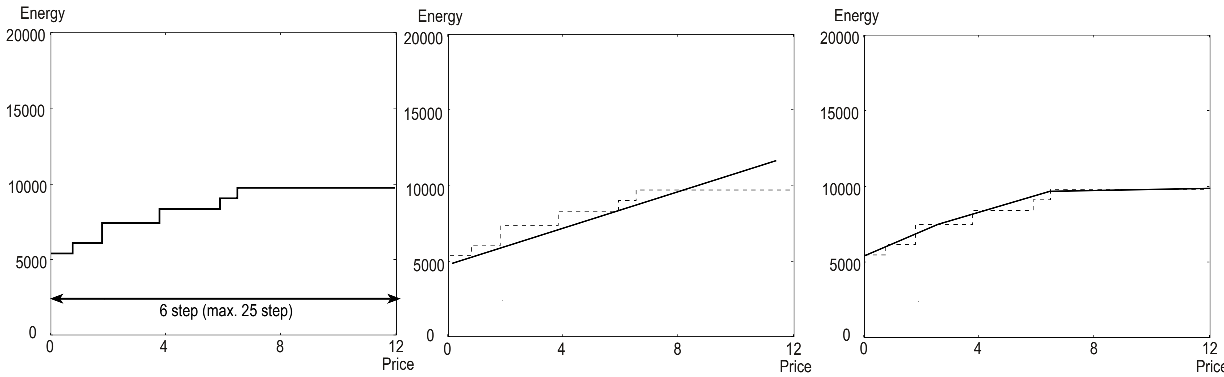

Figure 1: Actual (left), linear (center) and polygonal supply curves (right). Representation by a polygonal line is closer to reality than the linear supply and does not depend on an excessive number of parameters.

depending on labor hours and daylight), the day of the week (the dependence between labor hours and demand changes on weekends and holidays) and the season (electrical cooling or heating, affects both previous dependencies).

Given this information, we decided to stay in an intermediate position between (a) assuming that the supply curve is always the same for each agent, and (b) assuming a different curve for every market. Since (a) is too imprecise and (b) is intractable, in this work we will allow each agent to select its curve from a restricted set of choices, depending on the values of the features mentioned before. In other words, a strategy comprises:

- a rule-based classification system, that produces a segmentation of the market points into a certain number of classes depending on hour, day of the week and type of day, and

- as many supply curves as market segments.

That is, each individual is a set of rules whose antecedents are assertions with regard to market characteristics and whose consequents are the supply curves that the player can use. We shall call these consequents "prototype strategies".

The simplest representation of a prototype strategy is a straight line. Linear models can approximate the behavior of a competitive electrical market in the neighborhood of its equilibrium point. Unfortunately, in spite of this kind of simplification, which is valid for studying the response of the market under small changes, it is not accurate enough to estimate complete supply curves of the agents, which are highly non linear. We have decided to use piecewise linear supply curves instead (see Figure 1.) Their number of segments will be a compromise between the accuracy of the model and the amount of available data (three segments in most of the experiments in this paper.)

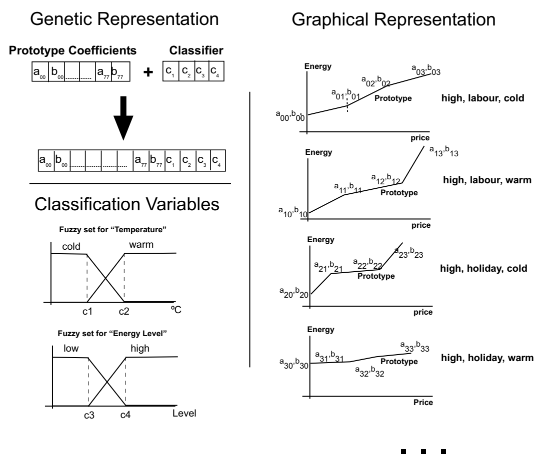

Figure 2: Polygonal supply curve comprising three segments and a classifier with three variables that segments the markets into 8 clusters; (top left) genetic representation, (bottom left) classifier variable values, (right) graphical representation.

3.2.2 Genetic representation

Each individual in the coevolutionary approach [7], [9] codifies a possible set of strategies (i.e., a fuzzy-rule-based classifier system and a set of prototype strategies) of one of the agents; we will keep as many populations of individuals as agents exist. Fitness is not assigned to an individual but to a combination of individuals extracted from all populations [10] [11].

An individual in the coevolutionary approach will be codified with a chain of numbers. This chain comprises two real numbers to define every segment in a prototype, plus a list containing the numerical parameters on which the linguistic terms in the antecedents of the classifier depends.

An example in showed in figure 2 for one firm with a classifier based on tree variables: "Energy level" (fuzzy), "Type of day" (crisp) and "Temperature"(fuzzy).

3.2.3 Genetic operators

Individuals in the coevolutionary approach are represented by chains of real numbers, thus there is no need to define custom genetic operators. However, the relative sizes of the subchain codifying the consequents and the subchain codifying the list of parameters of the classifier are very different. We have opted to let only one of these parts be modified in every genetic operation, thus we can manually balance the evolution of both and speed up the evolution of the classifier part. This is the only difference between our operators and the standard versions of uniform arithmetic crossover and mutation [12][13].

When two individuals are to be crossed, a coin is tossed to decide whether we select (a) the subchain codifying the classifier definition or (b) one subchain that codifies the definition of one of the prototypes. The selected subchains are recombined by means of standard arithmetic crossover, but the remaining part of the individual remains unchanged.

The mutation operator is defined as the crossing of an individual with another one, generated at random.

3.2.4 Fitness function

Each firm has as an objective the maximization of its own profit, assuming that the unitary benefits are all the same. This decision implies that we need to rank strategies according to two different criteria. Let us compare two strategies f_1 and f_2 of the same firm: after playing games with either f_1 and f_2 and all strategies of the remaining players, an strategy f_1 is better than another one f_2 (a) the best aggregated profit of the remaining players against f_1 is lower than their benefit if f_2 is used (min-max strategy,) and (b) f_1 produces similar unitary profits for all players. “Unitary profit” is defined as the difference between cost and income, divided by the number of MWs sold. The first goal measures the benefits of a strategy in the worst case, and the second one measures the degree of fulfillment of the restriction “all unitary profits are the same.” We will use the profit of the strategy to quantify the first objective, and the mean of the variances of the unitary profits to quantify the second one.

Different methods exist for mapping multi-objective fitness into scalar fitness [8]. We have studied the weighted average of values (a) and (b), but, according to our experiments ,[3], there is a significant improvement if we use a multi-objective approach instead [6].

4 Numerical Results

This section describes the application of our method to a semi-synthetic problem componed by 40 market points. This problem was designed to reproduce current scenarios in the Spanish electrical market, while being originated by theoretical data, thus we can assess our results. The methods used here will be called “Reactive Equilibrium Coevolutionary Genetic Model” (RECGM), “Equilibrium Coevolutionary Genetic Model” (ECGM) and “Regression Coevolutionary Genetic Model” (RCGM). The first method is the one being proposed in this paper and tries to obtain the reacting supply curves when hard deviation are applied to one supply curve agent; the second one was proposed in [5], and obtains the optimal oligopolistic solution (Cournot solution); and the third one was proposed in [3], and obtains the actual supply curves being used in the market.

4.1 Applying the methodology

Three steps of the methodology presented in this work are applied to the semi-synthetic problem:

Step 1) RCGM is applied to our 40 market points to obtain an estimation of the supply curves of all agents, an also knows their actual profits and market share.

Step 2) Before, we select an agent to be modified. In this case, we decided to choose the greater profit agent.

Step 3) Finally, RECGM is run to obtain the reaction supply curves to previous step deviated supply curve.

Also, we will use ECGM model to calculate optimal profit and amount of energy for oligopolistic solution (Cournot solution), and detect illegal agreement between generators estimated.

4.1.1 Step 1

Individual strategies extracted by RCGM from 40 market points (price, energy, energy level, type of day, temperature) score 100% linguistic matching respect theoretical individual strategies used to generate market points. The mean perceptual error of estimated individual quantities for each market was 2.92% and the mean error of estimated energy share in each market was 0.69%. Profit, energy, market share for the competition of these estimated individual strategies can be see in table 1.

	Agent0	Agent1	Agent2	Agent3
Energy	98210.3	196062	141886	226314
Energy Share(%)	14.82	29.60	21.42	34.16
Profit	125191	**156961**	85585.2	135626

Table 1: Market share and profit for estimated supply curves agents (RCGM model)

We have select greater profit agent to apply the deviation, which is Agent1 with 156961.

4.1.2 Step 2

Results of competition of the strategies resulting from applying RCGM to semi-synthetic problem, RCGM to same problem with modified supply curve of Agent 1, and optimal equilibrium strategies calculated with ECGM are in table 2. It can be seen that modified RCGM pool obtains 12.7445% more profit than original RCGM pool generating 4.86588% less energy. Also we can see that our modified RCGM pool profits are lower than optimal pool pools, thus there is still room to obtain more benefits if supply curves are improved. Notice that the opposite result (better results than in the oligopolistic equilibrium) would have meant that two or more of the agents have signed an illegal agreement.

	Agent 0	Agent 1	Agent 2	Agent 3
ECGM Pool Profit	198143	197669	195047	252652
RCGM Pool Profit	125191	156961	85585.2	135626
Modified RCGM Pool Profit	136020	176964	102945	159531
% Profit Variation	+8.65029	**+12.7445**	+20.2836	+17.6252
% Global Profit Variation	+14.3232			
RCGM Pool Energy	98210.3	196062	141886	226314
Modified RCGM Pool Energy	103366	186522	142235	225119
% Energy Variation	+5.24978	**-4.86588**	+0.246243	-0.528113
% Global Energy Variation	-0.789489			

Table 2: Energy and Profit Comparison for ECGM, RCGM and Modified RCGM Resulting Pools

4.1.3 Step 3

Now, we have to simulate the reaction of the competing not modified strategy agents to the changed strategy (Agent 1). Results of competition of the strategies resulting from this simulation can be seen in table 3. Notice, that reactive pool, "Modified RECGM Pool", is obtains lower profits, both individual and global profit, than modified pool ,"Modified RCGM Pool". The reason for this situation, is that "Modified RCGM Pool" has been select by hand, thereby modified strategy curve; instead the reactive strategies, "Modified RECGM Pool", are calculated by the equilibrium algorithm RECGM depending on the selected by hand modified strategy. Also, we run the reactive algorithm, RECGM, but with not modified studied strategy, and the results were worse than "Modified RECGM pool" (see table 4).

	Agent 0	Agent 1	Agent 2	Agent 3
Modified RCGM Pool Profit	136020	176964	102945	159531
Modified RECGM Pool Profit	68870.4	134561	118648	109580
% Profit Variation	-49.3674	-23.9613	+15.254	-31.3107
% Global Profit Variation	-31.7781			
Modified RCGM Pool Energy	103366	186522	142235	225119
Modified RECGM Pool Energy	108136	186908	171816	171221
% Energy Variation	+4.61455	+0.20677	+20.7969	-23.9418
% Global Energy Variation	+4.72133			

Table 3: Energy and Profit Comparison for RCGM and Modified RECGM Resulting Pools

4.1.4 Resume

By the last, we compare results from reactive pools for Not Modified Studied Strategy and Modified Studied Strategy, calculated with RECGM, (see table 4). It can be seen that “Modified RECGM Pool” obtains 33.7634% more profit than “Not Modified RECGM Pool” generating 0.53552% less energy, i.e. the reaction for modified strategy is better that reaction for not-modified strategy. Also, the modified strategy agent (Firm 1) obtains 25.1091% more profit that not-modified strategy agent (Firm 1), generation 5.72111% less energy.

	Agent 0	Agent 1	Agent 2	Agent 3
Not Modified RECGM Pool Profit	54707.8	107555	76044.9	84396.3
Modified RECGM Pool Profit	68870.4	134561	118648	109580
% Profit Variation	+25.8879	**+25.1091**	+56.0234	+29.8402
% Global Profit Variation	+33.7634			
Not Modified RECGM Pool Energy	116536	198250	157643	169087
Modified RECGM Pool Energy	108136	186908	171816	171221
% Energy Variation	-7.20822	-5.72111	+8.99041	+1.26211
% Global Energy Variation	-0.53552			

Table 4: Energy and Profit Comparison for Not Modified RECGM and Modified RECGM Resulting Pools

5 Concluding Remarks

The methodology proposed here serves improve the profit of an electrical company by adjusting it to the supply in terms of an oligopolistic market. Also, a competing firm can apply hard deviations to its strategy and simulate the reaction of the remaining strategies. Experiments presented show that the Reaction Pool calculated with presented methodology obtains more profit for all agents when higher deviations are applied to studied strategy. Moreover, this methodology may also serve to the Market Operator, because the estimation of the theoretical maximum profit and its comparison to the actual situation can be used to detect illegal agreements between generators.

Acknowledgements

This work was funded by Spanish M. of Science and Technology and by FEDER funds, under the grant TIC-04036-C05-0.

REFERENCES

[1] A. Cournot. *Recherches sur les Principies Mathmatiques de la Thorie des Richesses.* Hachette, Pars, 1838.

[2] Ministerio de Industria y Energía. Protocolo para el establecimiento de una nueva regulacin del sistema electico nacional. Technical report, Ministerio de Industria y Energa, 1996.

[3] E.A. de la Cal and L. Sánchez. Generative offers estimation using coevolutive genetic algorithms in tha spanish electrical market. *Applied Intelligence (Admitted for publication)*, 2003.

[4] E.A. de la Cal y L. Sanchez Ramos. Discusión y aplicación práctica de un modelo de estimación de estrategias de generación eléctrica. In *Segundo Congreso Espanol de Metaheurísticas, Algoritmos Evolutivos y Bioinspirados.*, pages 47–53, Gijón, 2003.

[5] E.A. de la Cal y L. Sanchez Ramos. Optimizing supply strategies in the spanish electrical market. In *International Work on Artificial Neural Networks, 2003*, Menorca, 2003.

[6] C. M. Fonseca and P. J. Fleming. Multiobjective Optimization and Multiple Constraint Handling with Evolutionary Algorithms—Part II: A Application Example. *IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans*, 28(1):38–47, 1998.

[7] W. D. Hillis. Co-evolving parasites improves simulated evolution as an optimization technique. *Artificial Life II*, pages 41–47, 1991.

[8] Y.-J. Lai and C.-L. Hwang. *Fuzzy Multiple Objetive Decision Making: Methods and Applications.* Springer-Verlag, New York, 1996.

[9] K.A. De Jong M.A. Potterm and J.J. Grefenstette. A coevolutionary approach to learning sequential decision rules. *ICGA95*, 1995.

[10] J. Paredis. Coevolutionary computation. *Artificial Life*, 2(4):355–375, 1995.

[11] C.D. Rosin and R.K. Belew. New methods for competitive coevolution. *Evolutionary Computation*, 5(1):1–29, 1997.

[12] W. M. Spears and K. A. De Jong. On the virtues of parameterized uniform crossover. In Rick Belew and Lashon Booker, editors, *Proc. 4th Int. Conf. on GA*, pages 230–236, San Mateo, CA, 1991. Morgan Kaufman.

[13] G. Syswerda. Uniform crossover in genetic algorithms. In Rick Belew and Lashon Booker, editors, *Proc 3th Int Conf on GA*, pages 2–9, San Mateo, CA, 1989. Morgan Kaufman.