Optimizing supply strategies in the Electrical Spanish Market

Enrique A. de la Cal Marín and Luciano Sánchez Ramos

Universidad de Oviedo, Dpto. de Informática, Laboratorio de Metrología y Modelos,
Campus de Viesques, 33203 Gijn, España,
delacal@etsiig.uniovi.es
luciano@ccia.uniovi.es

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".
En este trabajo se presenta un modo basado en algoritmos genicos que nos permite simular situaciones de equilibrio a la Cournot en el pool eltrico espaol suponiendo un comportamiento oligopoltico perfecto de los agentes. Mediante el modelo genico anterior calcularemos las curvas de generacin ptimas individuales de los agentes competidores.

1 Introduction

The cost of production of electrical energy depends on the type of generator: one MW produced by a nuclear plant costs less than one MW produced by a thermal plant. The most economical plants are in operation most of the time while the more expensive ones connect to the electrical system only when the former cannot cover demand. Consequently, the cost of energy is higher during peak consumption and lower during the hours of less demand, for instance at night.

Many other factors intervene in the selection of the power plants that connect to the system at any given time, such as geographic location, which affects the loss of energy in the transport lines, or the precipitation rate with regard to the operation of hydraulic plants. In spite of this, the basic principle that "the cheaper power plants connect first" explains the majority of the fluctuations in the cost of energy.

The relationship between the cost of production and the selling price 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 [?], 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 again 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”.

En el presente trabajo proponemos una nueva herramienta que nos permite estimar la ofertas de equilibrio, suponiendo un comportamiento oligopolista perfecto de los agentes. Para ello nos basaremos en una estimacin de las demandas horarias de energ ascomo en las horas de consumo, la temperatura del aire y el d de la semana. Este modelo de estimacin nos permite simular el comportamiento de un pool cuando se aplican modificaciones sensible en las estrategias que compiten en .

En nuestro trabajo [?], propusimos una herramienta inteligente de anisis datos capaz de estimar las ofertas pasadas de los agentes de un pool basdonos en los precios de la energ y las horas de consumo. Este otro modelo slo nos permit simular ligeras variaciones de las estrategias, ya que se trataba de un modelo de regresin.

1.1 Sumario

The remainder of this paper is arranged as follows: In Section 2, the problem to solve is explained. The “casation process” in term of Games Theory is described in Section 3. Our methodology is described in Section 4. In Section 5, a simple problem is solved to illustrate the use of the method proposed here and regression method and equilibrium method, applied to a semi-synthetic problem, are compared. El trabajo finaliza con el apartado de conclusiones y trabajos futuros.

2 Planteamiento del problema

2.1 El problema de Cournot

La competencia perfecta es un mecanismo de asignacin de recursos descentralizado, electricidad en nuestro caso, en el que los agentes -generadores y comercializadores- consideran los precios como datos y tos transmiten toda la informacin necesaria para que los agentes tomen sus decisiones de optimizacin -maximizacin de utilidad y de beneficio, respectivamente- de forma simultanea y mutuamente compatible, [?]. Las empresas, en general, tiene inter en que un mercado no funcione en forma competitiva. Parece bastante obvio que un agente cualquiera esten no ser un competidor que acte paramricamente respecto a los precios de los bienes que vende o compra, porque siempre preferirser monopolista en ambos mercados. El extremo contrario a un mercado de competencia perfecta es un mercado monopolista. Y en una tercera estructura de mercado, podrmos decir *intermedia*, estel oligopolio.

En la estructura de mercado oligopolista las empresas tienen el poder de determinar los precios, lo que diferencia al oligopolio de la competencia. Como adem, existe m de una empresa, cada una de ellas tomarsus decisiones bajo hiptesis respecto a cmo actuar sus competidoras o a cmo reaccionar las mismas cuando se comporte de una determinada forma, [**?**].

El supuesto de Cournot consiste en un duopolio basado en cantidades, en el que las empresas consideran nula la reaccin de sus competidores si ellas varn sus cantidades ofertadas. Esto lleva la competicin a una situacin de equilibrio, tambi denominada equilibrio de Cournot en el que las firmas no presentan incentivos para ofertar nada mejor. La solucin clica al problema original de Cournot se puede efectuar por modos analicos ya que las ofertas de los competidores son constantes y la curva de demanda es una nica recta. En cambio el equilibrio econmico de mercados eltricos oligopolistas reales no puede calcularse por modo analicos, [**?**], [**?**], por ello ha venido aproximando mediante modelos lineales. Las aproximaciones lineales son tiles para estudiar el comportamiento de un mercado eltrico cerca de su punto de equilibrio. De modo que estos modelos slo permitirn estudiar la respuesta del mercado bajo ligeros cambios del mismo, ya que introduce gran imprecisin cuando se estudian policas de generacin completas, las cuales son en general no-lineales. En este trabajo proponemos un modelo genico que permite estudiar la respuesta del mercado ante cambios bruscos en las estrategias de competicin.

2.2 Formulacin genica

En este trabajo, queremos estimar las ofertas de generacin individuales ptimas de los agentes que compiten en el pool eltrico a partir de un archivo de curvas de demanda. La estimacin se realizaren el supuesto de que las empresas se comportan como un oligopolio a la Cournot. To do this, a coevolutionary genetic algorithm is used.

Briefly, a genetic algorithm works as follows: first, we define as many populations of strategies as players. To score a strategy, we will simulate a game, making this strategy compete with una seleccin de pools de estrategias del resto de jugadores. La estrategia recibirsu puntuacin basada en dos criterios:

- La puntuacin m alta resultante de los juegos calculados.
- The unit profits obtained by each player are similar.

Observe that genetic algorithms have been applied to solve economic problems similar to the one considered int this paper (see [**?**], [**?**], [**?**], [**?**], [**?**], [**?**]) and a market model that shares some of the characteristics of this one has been related to a coevolutionary genetic programming-based model above [**?**]. Unfortunately, in our opinion, none of these approaches can be extended to solve the precise problem we pose here.

3 Formulacin del proceso de casacin en tminos de la teor de juegos

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 this hypothesis, 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. 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.

4 Metodolog

The algorithm studied in this work serves to obtain the optimal (in Cournot terms) supply curves of the companies competing in the market using demand curve of several previous markets. Dado que el objetivo de nuestro algoritmo es el cculo de las curvas de equilibrio, los nicos datos de entrada que necesitaremos ser la demanda para cada mercado del perdo estudiado y los costes de generacin de las empresas que compiten. Con estos datos podremos calcular los beneficios del juego de competicin para cada mercado.

Each supply curve represents a market strategy and the companies elaborate them based on their assumptions with regard to the evolution of demand and the strategies of the other competitors.

4.1 Definicin de la curva de generacin

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. Our analysis would be very imprecise if we did not consider some of these factors. Following our own experience, three features should be considered: the hour (which is related to the amount of energy negotiated, 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.) The number of their 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.)

4.2 Representacin genica

Each individual in the coevolutionary approach [?], [?] 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

Fig. 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.

as agents exist. Fitness is not assigned to an individual but to a combination of individuals extracted from all populations [**?**] [**?**].

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 depend.

To clarify the codification of an individual, let us consider the example in Figure 2. Let us suppose we have tree input variables, called “energy level” (fuzzy), “type of day” (crisp) and “temperature” (fuzzy).

Fig. 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.

The first variable can take values from 0 to 23 that represent the level energy order relative to the day, is used instead hour of the day, because "energy level" is not cyclic and can take linguistic values 'high' and 'low', the second one can take two linguistic values, “labor” and ”holiday” and “temperature”, also can take linguistic values, “cold” and ”warm”.

The antecedents of the rules that compound the strategy must span all values of the input variables; we discretize all continuous variables into linguistic terms first, and then enumerate all possibilities.

En el ejemplo de la figura 2 top left) el par (c_1, c_2) representa el soporte de la funcin de pertenencia de los valores simblicos de la variable difusa “energy level” (ver figura 2 bottom left), y el par (c_3, c_4) lo mismo para la variable “temperature”. La variable “type of day” al ser nido simblico estimplito y por lo tanto no tiene representacin genica.

```
if high and labor and cold
    then prototype=(a00,b00,a01,b01,a02,b02,a03,b03)
if high and labor and warm
    then prototype=(a10,b10,a11,b11,a12,b12,a13,b13)
if high and holiday and cold
    then prototype=(a20,b20,a21,b21,a22,b22,a23,b23)
if high and holiday and warm
    then prototype=(a30,b30,a31,b31,a32,b32,a33,b33)
if low and labor and cold
    then prototype=(a40,b40,a41,b41,a42,b42,a43,b43)
if low and labor and warm
    then prototype=(a50,b50,a51,b51,a52,b52,a53,b53)
if low and holiday and cold
    then prototype=(a60,b60,a61,b61,a62,b62,a63,b63)
if low and holiday and warm
    then prototype=(a70,b70,a71,b71,a72,b72,a73,b73)
```

and it can be codified by a chain of 68 numbers. Since each prototype strategy depends on eight values, we need 8×8 parameters to define all consequents and four more numbers to define the values of (c_1, c_2, c_3, c_4). The antecedents need not to be codified, because they are implicit in the sorting of the rules.

In general, a strategy depending on n input variables, taking n_i different values each, will be codified by a chain of $8 \prod_{i=1}^{n} n_i + C$, where C is the number of parameters defining the classifier.

4.3 Definicin de los operadores genicos

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 [**?**][**?**]. Observe that the offspring is always valid, because:

- The consequents produced by the either the mutation or the crossover operators are weighted sums of monotonic functions, which are also monotonic functions.
- The classifier arising from crossover or mutation is checked, and repaired if needed, so that all parameters defining it are constrained to their respective ranges.

Fig. 3. Crossover operations in coevolutionary (top) and evolutionary (bottom) representations. Evolutionary crossover consists of selecting one agent at random and performing the coevolutionary crossover over the corresponding parts.

When two individuals are to be crossed, a coin is tossed to decide whether we select from each of them (a) the subchain codifying the classifier definition or (b) one subchain that codifies the definition of one of the prototypes (the consequent of a single rule is modified after applying crossover.) The selected subchains are recombined by means of standard arithmetic crossover, but the remaining part of the individual remains untouched (see Figure 3 top.)

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

4.4 Definicin de la funcin de fitness

Hemos definido el problema de Cournot como un mercado competitivo donde todas las firma envn al mercado simulteamente su produccin siendo la demanda del mercado la que determinarel precio en funcin las cantidades producidas. Esto siempre supeditado a que cada firma tenga como objetivo maximizar su beneficio. Para estimar las estrategias de generacin que alcanzan el equilibrio de Cournot en funcin de un archivo de demandas definiremos un fitness que simule el comportamiento de los jugadores en el supuesto de Cournot.

We have mentioned that we needed to assume that the unitary profits of all firms are the same in order to obtain a good model. This decision implies that we need to rank strategies according to two different criteria:

a strategy is scored, after being combined with the strategies of the remaining players, (a) an strategy of firm f1 is better than firm f2 one when the best aggregated profit of the remaining players for f1 games if better than for f2 games,i.e. a kind of min-max strategy, (b) similar unitary profits are achieved by all players –where "unitary profit" is defined as the difference between cost and income, divided by the number of MWs sold. The first goal measures the worst situation for a firm, 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 [**?**]. We have studied the weighted average of values (a) and (b), but, according to our experiments ,[**?**], there is a significant improvement if we use a multi-objective approach instead [**?**][**?**][**?**][**?**].

5 Numerical Results

A simple problem is presented here for the sake of illustrating the basic aspects of the proposed methodology. This example models 10 repetitions of a game (Cournot equilibrium search) in which we know each player, four players like Spanish Market, always uses the same supply curve, thus we do not need the classifier. Supplies are straight lines, each depending on two parameters.

Table 1. Equilibrium Market Point Calculated by Analitical Method

Market	0	1	2	3	4	5	6	7	8	9
price	3,3	4,1	4,9	5,71	6,5	7,4	8,2	9,1	10,0	10,8
energy	1720,7	1925,7	2115,2	2292,3	2459,3	2617,6	2768,5	2912,9	3051,7	3185,4

The inputs for this problem are:

1. The cost functions. q is the quantity of energy produced, C_0 to C_3 are the prices demanded: $C_i(q)\& = \&(4+i)e - 6q^3$
2. The market scenario, a series of 10 demand functions (D_m) with the same elasticity (i.e., the same steepness):
$$D_m(p) = -1000p + (5000 + 1000m), \quad \text{for } m \text{ in } 0 \ldots 9$$
3. The set of Cournot Market Equilibrium points in table 1, (price$_i$, quantity$_i$). They were generated from the intersections of the demand functions (D_i) and the aggregate strategy of the equilibrium individual strategies.
4. Y por ltimo, las estrategias de equilibrio, calculadas analicamente, con las que compararemos la salida de nuestro algoritmo son las de la tabla 2.

Now, estimated equilibrium individual strategies were obtained after running the coevolutionary algorithm with four populations with the size of 1000,

Table 2. Equilibrium Curves calculated by Analitical Method for 10 Market Points

Market	Firm0	Firm1	Firm2	Firm3
0	150,43p	134,58p	115,46p	124,25p
1	135,57p	121,27p	103,92p	111,87p
2	124,26p	111,13p	95,16p	102,46p
3	115,29p	103,11p	88,22p	95,00p
4	107,96p	96,55p	82,56p	88,92p
5	101,84p	91,06p	77,83p	83,84p
6	96,62p	86,39p	73,80p	79,51p
7	92,10p	82,36p	70,32p	75,77p
8	88,15p	78,82p	67,28p	72,50p
9	84,66p	75,69p	64,59p	69,61p

Cournot multicriteria fitness, 400 generations, tournament selection (size 4) and linear descending crossover probability, from 100% to 0%. The output of our method is:

$$\begin{aligned} q'_0(p) &= 67.1636p + 226.987 \\ q'_1(p) &= 56.4915p + 234.217 \\ q'_2(p) &= 45.5331p + 272.999 \\ q'_3(p) &= 41.5025p + 258.445 \end{aligned}$$

Donde cada estrategia se aplicarpara los 10 mercados del problema, D_m.

Fig. 4. Curva de oferta agregada de equilibrio resultante de aplicar CGM con fitness Cournot a conjunto de 10 mercados

En la figura 4 se representan los puntos de equilibrio calculados analicamente (ver tabla 1) y la curva agregada de equilibrio estimada con nuestro algoritmo. Observamos la buena aproximacin de la solucin obtenida mediante estrategias lineales a la nube de puntos no-colineales. En concreto el error medio de los puntos de equilibrio estimados respecto a los puntos de equilibrio reales ha sido de 2.65361% por mercado y firma respecto a la dimensin cantidad. The mean percentage error of estimated individual quantity for each market was 5.93207% and the mean percentage error of estimated energy share in each market was 1.11367%.

5.1 Semi-synthetic problem

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 supply curves, thus we can quantify the accuracy of regression and equilibrium methods and compare its results. From now on, methods proposed will be called " "Equilibrium Coevolutionary Genetic Model" (ECGM) and "Regression Coevolutionary Genetic Model" (RCGM).

En la tabla 3 se recogen los resultados de aplicar los modos RCGM y ECGM al problema semi-sintico.

El pool recabado mediante el modelo RCGM a partir de los 40 puntos de mercado (price, energy, energy level, type of day, temperature) obtuvo un ito del 100% de acierto al hacer un matching lingütico de las reglas individuales tericas, y los errores porcentuales medios de estimacin de cantidades individuales y cuotas de mercado fueron de 2.92% y 0.69% respectivamente.

Si comparamos los resultados de la competicin de ambos pools (ver tabla 3), podemos ver que el pool ECGM a costa de generar un 16.716% menos de energ podr obtener un 159.852% m de beneficio que el modelo RCGM. Lo cual nos permite concluir que las estrategias que han generado los puntos de mercado de estudio son muy mejorables.

Table 3. Energy and Profit Comparison for RCGM and ECGM Resulting Pools

	Firm 0	Firm 1	Firm 2	Firm 3
ECGM Pool Profit	198143	197669	195047	252652
RCGM Pool Profit	125191	156961	85585.2	135626
% Profit Variation	-36.818	-20.5943	-56.1208	-46.3189
% Global Profit Variation	-159.852			
ECGM Pool Energy	140347	148200	145383	193681
RCGM Pool Energy	98210.3	196062	141886	226314
% Energy Variation	-30.0231	+32.2956	-2.40524	+16.8487
% Global Energy Variation	+16.716			

6 Concluding Remarks and Future Work

Coevolutionary genetic models are usually used to simulate natural systems with multiple agents of independent behavior, where mathematical models are too complex to be applied. Here, we have experimentally shown that a coevolutionary genetic model can achieve the Cournot equilibrium for a set of electrical markets (a market is a demand curve) with a only a linear curve without classifier per player (ECGM). Also we have extended the application of the ECGM to a set of markets characterized with three variables: "energy level", "type of the day" and "temperature". In this second case we incorporate fuzzy classifier, depending of the variables, to the individual supply strategies. After that, we defined prices for all the markets and run RCGM to recover fuzzy individual supply strategies, and then run ECGM to calculate equilibrium fuzzy individual supply strategies. We show that equilibrium individual supply strategies (ECGM) improves profit RCGM strategies in 159.852%.

From the point of view of a firm that manages our equilibrium model, this method allows it simulate a large changes in its supply curves, given a certain market situation. This way, a firm can adjust its strategy and improve its profits.

From the Market Operator's point of view, it is useful to know the Cournot equilibrium strategies for a set of market points in a perfect oligopolistic situation, which is a non-linear extension to the Cournot problem [**?**]. This information serves to estimate the difference between the real profit of the pool and the theoretical maximum profit if competition is perfect, therefore detecting illegal agreements between generators.