Coevolutionary Genetic Fuzzy System to Assess Multiagent Bidding Strategies in Electricity Markets

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Abstract— *In this paper we study a genetic fuzzy system approach to assess suitable bidding strategies for agents in online auction environments. Assessing efficient bidding strategies allows evaluation of auction models and verification whether the mechanism design achieves its goals. Day-ahead electricity auctions are particularly explored to give an experimental instance of the approach developed in this paper. Previous works have reported successful fuzzy bidding strategies developed by genetic fuzzy systems and coevolutionary algorithms. Here we review the coevolutionary algorithm and present recent results of the bidding strategies behavior. We analyze how the evolutionary strategies perform against each other in dynamic environments. Coevolutionary approaches in which coevolutionary agents interact through their fuzzy bidding strategies permit realistic and transparent representations of the behavior of the agents in auction-based markets. They also improve market representation and evaluation mechanisms. Experimental results show that coevolutionary agents can enhance their profits at the cost of increasing system hourly price paid by demand, an undesirable outcome from the perspective of the buyers.*

Keywords— Genetic fuzzy systems, electricity markets, auctions, multiagent systems, computational economics.

1 Introduction

The restructuring process of electricity markets has raised new challenges and opportunities, because currently there is no consensual market architecture. The progress of the power industry has mirrored the lack of insight about the mechanism design issues to be addressed. An electricity market is inherently a complex system populated by self interested, interacting economic agents. Tools rooted in the neoclassical economic theory have shown to be of limited value to study the behavior of economic agents in electricity markets. The approach considered in this paper is derived from agent-based computational economics (ACE) [15] and computational intelligence tools. The purpose is to find bidding strategies for a set of agents playing in a market using genetic fuzzy systems principles. The approach can be extended to other negotiation environments and contexts.

Evolutionary bidding strategies support decisions of market players and may uncover unknown and unexpected agents behaviors that help designers to simulate and analyze negotiation mechanisms. When coevolutionary agents extract benefits of strategic behavior, the mechanism designer can review the decision making process to correct eventual unfavorable decisions and fix mechanism flaws.

Recently a coevolutionary approach was suggested to assess bidding strategies for multiagent systems. The focus was on strategies encoded in fuzzy rule-based systems [18]. The aim was to learn models represented by coevolving knowledge bases and improve the performance of the agents when acting in competitive environments. In competitive environments data for learning and tuning of knowledge bases are rare and rule bases must evolve jointly with databases. An evolutionary algorithm whose operators use a variable length chromosome, a hierarchical relationship among individuals through fitness, and a scheme that successively explores and exploits the search space along generations has also been developed [17]. In this paper we first review the coevolutionary algorithm of [18], summarize recent results of coevolutionary bidding strategies, and analyze how evolutionary agent strategies react against each other in dynamic environments.

Electricity auctions are the main application example addressed in this paper due to its practical relevance and the experimental instance they provide. The example illustrates the design of bidding strategies to exploit the negotiation space and to take advantage of market power aiming at improved negotiation mechanisms.

This paper is organized as follows. After this introduction, a brief overview of strategic bidding and survey of related work are presented in section 2. Next, section 3 summarizes the approach addressed in this paper. Section 4 presents and discusses the experimental results. Section 5 concludes the paper and suggests issues for further research.

2 Evolutionary Techniques for Electricity Market Bidding Strategies

Currently, many power industries worldwide use auctions as a mechanism of resource allocation and system coordination. The design of auction mechanisms can give agents the ability to explore market imperfections for gaming.

A energy supplier (generator) competing in an electricity market has to decide upon how much energy to offer and at which price. In a perfectly competitive market, risk averse agents have an incentive to offer energy at a price equivalent to their marginal costs [7]. Electricity markets are, however, much more an oligopoly than a laissez-faire, with low or no demand elasticity in the short term, barriers to entry, and physical constraints. Thus, a energy supplier may have an incentive to offer energy at a price other than its marginal costs and to extract some surplus from such an imperfect market.

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The behavior of a generator bidding other than marginal costs in an effort to exploit market imperfections is defined as strategic bidding [6]. The most common strategy is to maximize the expected profit but other strategies may interest a supplier exercising its market power such as competing for being a base-load generator, increasing market share, increasing profit margin, etc.

2.1 Related Work

Evolutionary approaches for strategic bidding in electricity markets have been addressed in the literature in the realm of genetic algorithms, evolutionary strategies, and classifier systems. Multiagent system approaches have been proposed to model the electricity market as well, among them [8, 14].

The evolutionary strategy approach suggested in [19] evolves a single bid value, assumed to be valid for all hours of a day ahead market. In this sense, it does not give a bidding strategy, but a bid value that is narrowly valid for a specific situation.

The approach proposed in [1] is a classifier system capable of dealing with the grid constraints of the UK market and electrical restrictions that constraint generators to be *on* or *off* by the dispatch.

In [3] a coevolutionary approach based on a coevolutionary cooperative genetic algorithm (CCGA) is devised to analyze electricity market equilibrium. Results for a 3-firms market is presented. They show that the approach finds Cournot-Nash equilibrium and Pareto solutions. In a related work [4] the same coevolutionary CCGA scheme is used together with a Cournot model and a supply function equilibrium (SFE) model of a 5-firms experiment. In this case, the coevolutionary scheme converges to a Nash equilibria.

The coevolutionary approach to model the electricity market can be based on different coevolutionary methods such as the one addressed in [2] for duopolies. In this method, discretization of the state space imposes limitations.

The coevolutionary process proposed in [11] is more complex[1]. The intent is to coevolve agents strategies and market mechanisms. The authors use a genetic programming (GP) method to evolve a function the auctioneer uses to set the price between the ask and the bid price in a double auction framework. GP is used to represent the auctioneer and traders (buyers and sellers). Simulation results based on the Nicolaisen's experiment report a function with several terms after 10,000 generations. The authors claim that the function evolved was approximately equivalent to a discriminatory price k-double auction with $k = 0.5$.

3 Coevolutionary Fuzzy Bidding Strategies

The approach employed in this paper is to coevolve fuzzy bidding strategies. Previous work [17] has devised evolutionary fuzzy bidding strategies. In [18] a coevolutionary algorithm was introduced to study how the evolving strategies react against each other in dynamic bidding environment[2]. Contrary to alternative evolutionary approaches, the aim was to model bidding information and strategies within the framework of fuzzy set theory. By enabling a fuzzy system to learn trough an evolutionary algorithm, one expects to find effective and transparent bidding strategies. We assume that bidding strategies are encoded by fuzzy rule-based systems (FRBS). As opposed to trial and error methods, genetic algorithms are especially attractive to develop bidding strategies because they can optimize the knowledge base (dimension, membership functions and rules) for a given market configuration. Genetic algorithms are also more appropriate than conventional optimization techniques because rule base tuning may involve operators and high dimensionality search spaces.

Here a GFRBS (Genetic Fuzzy Rule-Based System[3]) scheme is adopted to simultaneously evolve the data base (granularity and membership functions) and the rule base of a FRBS with the aim to find the most profitable bidding strategy. Each population of the GFRBS is a coevolving specie that represents a market agent. The result is a set of fuzzy rule-based systems able to handle imprecise data typically found in auction environments.

The evolutionary approach detailed in [17] is used to evolve the data base employing a variable length chromosome to represent the rule base. In the rule base, both, the number of rules and size of each rule may change during the evolutionary process. A particularly suitable crossover operation detailed in [17] was developed to enhance system performance.

Many coevolutionary approaches emphasize explicit competition such as the host-parasite scheme to minimize sorting networks in [10]. The coevolutionary approach focused in this paper is based on the CCGA of Potter and De Jong [13]. As detailed below in Algorithm 1, our approach selects a representative agent for each coevolutionary specie. The species model bidding agents. The representatives are the ones who compete in the auctions. When representatives bid, their strategy may improve the profit of the remaining bidders. Thus, the remaining coevolutionary species may act in a tacit cooperation in this competitive game. Therefore, although CCGA was originally developed to coevolve subcomponents of a problem in an explicit cooperative framework, we use its main idea in a competitive environment: auction in electricity markets[4].

3.1 Genetic Algorithm

The genetic algorithm employed in this paper uses a variable length chromosome representation for both: data base and rule bases. The encoding schemes are similar to the ones adopted in [17]. Crossover operations in data base and rule base are synchronous, that is, crossover points of database and rule base induce exchange of chromosome portions to keep the rule structure and fuzzy terms meaningful in their offspring.

The first step to design a GFRBS must decide which part of the FRBS will be optimized by the genetic algorithm [5]. This decision usually means a trade off between granularity and search efficiency. In the approach adopted here, the following FRBS components are evolved: database (granularity and membership functions parameters) and rule base (number of "active" rules[5] and rule structure).

[1] A more complete report of this work can be found in [12].

[2] This and all previous papers are a result of the PhD thesis of the first author and has no links with the Regulatory Agency.

[3] For a taxonomy, a comprehensive survey of past and recent developments, as well as future trends of genetic fuzzy systems see [9].

[4] A similar approach was adopted in [3].

[5] An "active" rule is a rule that is processed during fuzzy inference while an "inactive" rule remains in the rule base genotype but it is not used during fuzzy inference.

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The GA also assumes the simultaneous evolution of the FRBS in the sense that each individual represents a complete fuzzy rule-based system as in the Pittsburgh approach. The FRBS is encoded in a chromosome Cr composed by three major components (Cr_1, Cr_2, and Cr_3) to represent the data and rule base.

More specifically, the chromosome component Cr_1 encodes granularity in a variable length chain of integers, and Cr_2 encodes membership functions parameters in a variable length chain of real numbers. The number of rules, rules size and the rules themselves define chromosome component Cr_3. Component Cr_3 has, in addition to two integers (number of rules and rules size), several variable chains of alleles of '0' or '1', where a '1' means that a linguistic term is used in the rule, otherwise it is '0'.

Algorithm 1 Coevolutionary GFRBS Algorithm

```
t ← 0
for each specie s do
   create random initial population Ω_0^s
end for
repeat
   for each specie s do
      for each specie r such that r ≠ s do
         choose a representative in Ω_t^r
      end for
      evaluate each individual in Ω_t^s through fitness function
      with the chosen representatives
      select parents in Ω_t^s based on relative fitness in Ω_t^s
      apply crossover and mutation on parents to produce
      offspring Ω_{t+1}^s
      t ← t + 1
   end for
until (stop criteria is satisfied)
```

As stated before, the coevolutionary algorithm detailed in Algorithm 1 is based on CCGA [13]. The specifics of the genetic operators are described next.

3.2 Genetic Operators

Due to the particular chromosome encoding structure used to represent the knowledge base, the nature of the genetic operators becomes an important issue to effectively evolve the FRBS. Since there are strong relationships among chromosome components, we need operators that work cooperatively on the chromosome.

Selection is performed using *roulette wheel*. We adopt an elitist model, but the best individual is not guaranteed to be selected for crossover, albeit kept intact in the offspring.

Crossover of the database follows the approach detailed in [17]. Summing up, two different crossover operators are used depending on whether the selected individuals have the same granularity or not. When the granularity is the same, a promising zone in the search space is found and must be appropriately exploited. In this case, the granularity of the offspring database (Cr_1) is kept the same and the membership functions parameters (Cr_2) combined following the max-min-arithmetic algorithm of [17]. When the selected pair has different granularity, a random crossover position p is chosen. Both, granularity (Cr_1) and the corresponding parameters of the membership functions (Cr_2) are recombined. Crossover operations of database and rule base are synchronous: crossover points of database and rule base induce exchange of chromosome portions that keep the rule structure and terms meaningful in their offspring.

Different operators can be used to mutate chromosomes, similarly as reported in [17]: a local variation is introduced to the granularity by adding or subtracting one with equal probability, mutation of membership function parameters uses the Michalewicz non-uniform mutation operator, and rule bases are mutated via the standard, bitwise reversing operation.

3.3 Electricity Market

The application example focused in this paper is electricity markets. The approach can, however, be extended to distinct negotiation applications. The coevolutionary GFRBS agents are thermal power suppliers that have to decide how to bid in auctions. The coevolutionary GFRBS species were evolved using a day-ahead electricity auction. We assume that the remaining agents are non evolutionary and conservative competitors. Conservative agents offer energy bidding all their capacity at their marginal costs [7]. The negotiation protocol is an uniform price sealed bid auction: the price paid for the energy is the same for all accepted bids and is equal to the last bid accepted. The auctioneer decides the hourly dispatch choosing the electricity generator agents outputs and the corresponding price to minimize overall energy cost. Cost minimization results in a merit order dispatch procedure, i.e., bids at lower prices come first. The performance of the best FRBS obtained were verified using test demand data for two weeks day-ahead auctions against conservative and evolutionary competitors. The results are presented and discussed in section 4.

The experiments use actual public data made available from the Brazilian Independent System Operator (ISO)[6]. Demand is supposed to be known to all the participant agents. The data used to evolve the GFRBS is the load of the week beginning on May 19th, 2002, for a portion of the national grid: the South sub-market. The fitness of the coevolutionary agents are the profit on the electricity auction of the decoded GFRBS for the training week. The best individual found by training is tested using the next two remaining weeks period that begins on May 26th 2002 [7].

3.4 Cost Function

A pool of power generator agents was setup based on actual, ISO's publicly available data. Electrical constraints and geo-electrical location are neglected in this work: all the plants are supposed to be in the same sub-market. There is some excess of supply and the running costs of producing electricity in coal, gas and oil plants have been modeled as quadratic functions of the power P_s supplied by the agent, expression (1). Nuclear plants are assumed to have linear cost functions.

$$F(P_s) = a + bP_s + cP_s^2 \quad \text{[GJ/h]} \tag{1}$$

The supplier cost function $C^j(.)$ is given by $F(P_s)$ multiplied by the fuel cost in \$/GJ. Hence costs are quadratic func-

[6] ONS: Operador Nacional do Sistema.

[7] These same data set was used in [17, 18]. Data set contains 504 samples; 168 used for training and 336 for testing.

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Table 1: Thermal power generator agents characteristics and cost functions.

Plant	Type	Capacity (MW)	Marginal cost ($/MWh)	$C^j(.)$
Ibirité	Gas	766.5	39.065	$3,632.08 + 31.966g + 0.00463g^2$
TermoRio	Gas	824.7	39.109	$3,904.05 + 31.912g + 0.00436g^2$
Argentina I	Gas	1,018	41.045	$4,459.61 + 32.775g + 0.00406g^2$
Argentina II	Gas	1,000	41.046	$4,379.82 + 32.774g + 0.00414g^2$

tions given by (2), where g_h^j is the amount supplied by agent j at hour h.

$$C^j(g_h^j) = \alpha + \beta g_h^j + \gamma {g_h^j}^2 \quad [\$/h] \tag{2}$$

3.5 Competitive Environment

We assume power demand D_h inelastic with price. Therefore, the auctioneer must assure, as commonly found in a single buyer auction, that for each hour h: $\sum_{j=1}^{T_h} g_h^j = D_h$, where g_h^j is the power supplied by agent j and T_h is the number of suppliers. Thus, allocation would cost the market $D_h \pi_h(D_h)$. The supplier agents profit is given by(3):

$$P_h^j = \pi_h g_h^j - C^j(g_h^j) \quad [\$/h] \tag{3}$$

Supplier agents (generators) must internalize all costs to a simple bid, a pair (q_h^j, p_h^j) of the amount offered (in MW) and its price ($/MWh), where the amount q_h^j is less than or equal to the agent capacity, G^j. Conservative agents bid a pair $(G^j, MC^j(G^j))$ where $MC^j(G^j)$ is the marginal cost at capacity G^j.

Table 1 shows the thermal generator agents characteristics for the agents we have chosen to coevolve. The complete data set of the thermal generation park can be found in [17]. The fourth column, the marginal cost ($/MWh), is the marginal cost at full capacity corresponding to conservative bids. The last column gives the cost functions of the thermal suppliers[8].

3.6 Fitness

Algorithm 2 Evaluation of Population Individuals

for each individual i such as $i \in \Omega_t^s$ **do**
  decode database and rule base of i as agent A_i
  add the agent A_i to the market
  simulate market (run auction) for the training period
  keep fitness F_{A_i} as the profit for the period
  remove A_i from the market
end for

The fitness of a GFRBS individual is defined as the profit of the corresponding agent during the training week. Algorithm 2 summarizes the evaluation of the fitness of each individual of the population.

4 Results

The experiments reported in this paper use a population of 40 individuals. Each individual encodes a single input-single output (SISO) FRBS: the input is the hourly load and the output

[8] g_h^j is denoted by g for short.

Table 2: Comparison between coevolutionary and conservative strategies.

conservative strategy			
agent	hours	energy (MWh)	profit ($)
Ibirité	332	232,954	849,960
TermoRio	277	199,390	959,133
Argentina I	202	179,595	1,065,262
Argentina II	149	116,381	1,049,804
coevolutionary strategy: testing			
agent	hours	energy (MWh)	profit ($)
Ibirité	334	255,856	2,082,681
TermoRio	336	248,367	2,237,294
Argentina I	150	89,969	1,825,135
Argentina II	335	301,710	2,304,976
variation: coevolutionary / conservative			
agent	hours	energy (MWh)	profit ($)
Ibirité	+0.60%	+9.83%	+145.03%
TermoRio	+21.30%	+24.56%	+133.26%
Argentina I	-25.74%	-49.90%	+71.33%
Argentina II	+124.83%	+159.24%	+119.56%

the corresponding the bid price. The genetic operators described in section 3.2 were employed in all the experiments[9] with probability of crossover 0.5 and probability of mutation 0.01. We let the evolutionary process run for 500 or 1,000 generations[10]. While several experiments were performed with 2 to 5 species, some of them did not achieve stable behavior. For instance, for 5 coevolutionary species stability was not attained after 1,000 generations. Section 4.2 discusses briefly why stable behavior may not be necessarily expected, as the 5 coevolutionary species case shows.

4.1 Experiment: Four Coevolutionary Strategies

In [18] two thermal plants coevolved. They are the same used as evolutionary agents in [17]: Argentina I and Argentina II, respectively.

Here we report an experiment in which Argentina I and Argentina II are coevolved together with other two natural gas plants: TermoRio and Ibirité. The fitness of the best individual of each specie during 1,000 generations of the evolutionary process (training period) is depicted in Fig. 1. Notice that, after a short unstable period lasting about 100 genera-

[9] The choice of the evolutionary parameters is not subject to any optimization process.

[10] The training process can take about 2 hours of processing time for 2 species, corresponding to 500 generations, and above 6 hours for 4 species and 1,000 generations. Experiments were done using a Pentium 4,2 GHz 256 Mb RAM PC running GNU/Linux Fedora.

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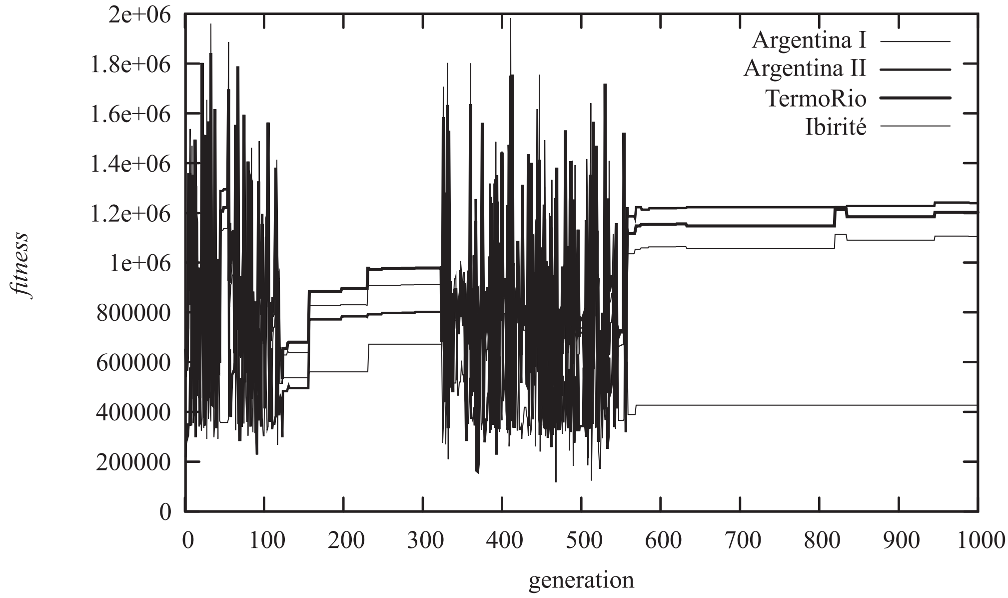

Figure 1: Fitness for coevolutionary species (4 thermal plants: Argentina I, Argentina II, TermoRio and Ibirité).

tions, the fitness of the best individual of each specie increases and stabilizes after about 200 generations and suddenly fitness behavior becomes unstable again. After approximately another 250 generations, the fitness becomes stable again, beginning at 550^{th} generation, and remains stable until the end of the evolutionary process window (1,000 generations). Notice also that the resulting outcome for the specie representing Argentina I becomes worse than in the one achieved during the first stable interval. This behavior suggests that the other three thermal plants may have learned how to exploit Argentina I agent weakness. All the remaining agents increase their profits. A close look at the fitness values shows that the species interact with each other during the whole evolutionary process.

After the end of the evolutionary process, the best individual of each specie is decoded into the corresponding bidding strategies to be played by the four agents. Table 2 summarizes the energy produced and profits obtained when the agents compete in the electricity market using the coevolutionary strategies. Table 2 shows how evolutionary agents outperform the corresponding conservative strategy of bidding their marginal costs at full capacity. The last four rows show the variation when using conservative and evolutionary strategies. We notice in Table 2 that Argentina I decreases energy production by half and still, with the hourly prices that result from the coevolutionary strategic bidding, increases its profit. This is a typical example of an undesirable behavior (from the perspective of the buyers) that mechanism designers wants to avoid before putting any market to work.

Clearly, the coevolutionary strategies affected the electric energy prices. The maximum hourly price of energy reached in the testing period was the same for both, purely conservative strategies or coevolutionary strategies, but coevolution made the average price 10.6% higher. The average price increase for the experiment reported in [18] was smaller, about 7.1%. Similarly as in [18], the individual hourly prices can be up to 53.2% higher for the coevolutionary strategies than purely conservative ones.

4.2 *Multiagent Learning Equilibrium*

It is important clarify that, while the results presented here and in [18] converge to a stable outcome, some of the experiments performed did not achieve stable outcome at all, remaining unstable for 500 or even 1,000 generations. Unstable outcomes typically occurred when there are many evolutionary agents (5 thermal generators in our experiments). While the dynamics of unstable behavior still is to be investigated, it does not seem to be a novelty, as it has been pointed out by Vidal in [16], who asserts that most multiagent learning systems do not necessarily converge to an equilibrium or stable behavior.

One reason for designers to use learning agents is because they do not know, at design time, the specific circumstances that the agents will face at run time. We will often see a multiagent system with learning agents when the designer can neither predict that an equilibrium solution will be found, nor which equilibria might emerge. The result is a form of closed loop feedback evolving system in which evolution and learning play a complementary role.

As stated in [16], the main reasons behind the difficulty to predict equilibrium solutions of a system include the existence of unpredictable environmental changes that affect the payoffs of the agents, and the fact that, in many systems, an agent only has access to its own set of payoffs. These reasons partially justify the difficulty a designer finds to predict equilibria, if any, a system could reach. However, the agents in a system may still play a game for which an equilibrium exists, even though the designer cannot predict it at design-time. Since in general the payoffs change, it is often the case that the agents are constantly modifying their strategies as an attempt to get better payoffs. This may result in unstable outcomes.

5 Conclusion

A coevolutionary genetic fuzzy systems approach to develop fuzzy bidding strategies was suggested in this paper. Coevo-

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lutionary approaches provide more realistic representation of agents in auction-based environments because they allow the bidding strategies to interact during the evolutionary process.

The results reported here for an electricity market example show that coevolution can improve agents profits at the expense of increasing the average electricity hourly price paid by demand, an outcome that is undesirable from the perspective of the buyers, and for auction based markets in general. Further research is needed to obtain design methods for bidding strategies in multiagent systems framework populated by intelligent agents. In particular, stability and equilibrium analysis of evolutionary learning in multiagent systems environments still remains a challenge.

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