# Modeling Dynamic Electricity Markets with Intelligent Agent Based Economics

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**Abstract:** In recent years, numerous competitive electricity markets have emerged around the world. Regulators need tools to help them study the impacts of their policy decisions on the physical operation and security of the power system, as well as the financial impact to the various market participants, and the economic aspects of the market itself (e.g., is it stable?). Alvarado [1] investigates the issue of market stability for simple market scenarios by setting up a set of dynamic market equations and computing the eigenvalues. This research begins by reproducing the results obtained from the dynamic market model, and suggests several extensions to make it more realistic. In addition, the authors propose that an agent-based approach to studying this market might reduce the number of assumptions required. This paper presents the steps in modeling agents that supply and demand electricity. This work discusses some of the benefits of using agent-based computational economics. The authors suggest some agent-based experiments to explore how changing the underlying assumptions, varying the pricing rules, and modifying the representation of the agent can produce changes to the results.

## 1 Introduction

Throughout the world, the electric industry is in the midst of major changes designed to promote competition. No longer vertically integrated with guaranteed customers and suppliers, electric generators and distributors will have to compete to sell and buy electricity. The traditional electric utilities of the past will find themselves in a highly competitive environment. Some countries and regions of the US (e.g., California, PJM) are already operating in a restructured environment. There does not yet appear to be a standardized final market structure that works for all areas, but each market that springs up adds to our experience and helps us make the next market implementation work a little better and more competitively. The authors believe that, to some degree depending on the market implementation, regional commodity exchanges will play a key role in buying and selling electricity.

Many questions about power system operation in an environment that is largely market-based remain unanswered. One such question is whether or not and under what conditions competitive electricity markets will be stable. Alvarado [1] investigated power system market stability and reported results showing that under certain assumptions and certain conditions, markets are predicted to exhibit stable behavior. To determine stability, a simple model of market participants was constructed and differential algebraic equations were employed to determine the equilibrium points of the system and boundary conditions on some of the variables. The general conclusions of [1] are that markets are stable as long as no producers or consumers exhibit significant economies-of-scale nor economies-of-consumption.

Many additional questions about market behavior in the presence of various regulations remain to be answered. This work begins with Alvarado's work on determination of market stability [1] for the market participants' reactions to market price and builds a simulation using the SIMULINK graphical simulation package in MATLAB in order to verify reported results and to explore the system dynamics.

The rest of this paper is organized as follows. Section 2 attempts to reproduce the work done by [1] algebraically. Section 3 performs simulations for the same simple cases that Alvarado presented, and highlights assumptions that must be made to perform the simulations. Results are generated using MATLAB's SIMULINK toolbox. Section 4 presents some general observations that the authors have made while simulating the markets and reproducing the results. Section 5 discusses why it might be very insightful to study the markets using adaptive agents. Section 6 suggests using genetic algorithms with a complex data structure (i.e., the GP-Automata) to represent and evolve the agents that would be participating in the market simulations. Finally, section 7 presents an overall summary of the paper, and gives some ideas for where this research could go in the future.

## 2 Predicting Stability with Control Theory

### *2.1 The Model / Assumptions*

In economics, aggregated supply and demand curves are constructed from individual supplier curves and individual demand curves, which are often represented in simple polynomial form. The total operating cost for a generator to produce some amount of power $P_g$ might be given by:

$$Cost_g \equiv a_g + b_g P_g + \frac{1}{2} c_g P_g^2$$

while the benefit to the consumer of some amount of power demanded $P_d$ would be:

$$Benefit_d \equiv a_d + b_d P_d + \frac{1}{2} c_d P_d^2$$

where the (1/2) has been explicitly put in because we are about to take the derivative of these equations in the next step.

However, what is also of interest are the marginal cost and the marginal benefit, i.e. the cost of producing an extra unit of the product and the value of one more unit to the consumer, respectively. These are given by taking the derivative of the cost and benefit equations above, thus marginal cost and marginal benefit are given by,

$$\lambda_g = b_g + c_g P_g$$

$$\lambda_d = b_d + c_d P_d$$

Alvarado [1] investigated stability of markets. For this, he makes three assumptions. First, that producers increase/decrease their output when the market price, λ, is above/below their marginal cost. Second, that consumers increase/decrease their consumption when the market price, λ, is below/above their marginal benefit. Third, that supply and demand are always in balance. For the case of one supplier and one consumer, these form three equations:

$$\tau_g \dot{P}_g = \lambda - \lambda_g$$

$$\tau_d \dot{P}_d = \lambda_d - \lambda$$

$$P_g = P_d$$

where $\tau_g$ and $\tau_d$ are proportionality constants. Alvarado uses them to indicate that each market participant responds in some finite amount of time, i.e. not instantaneously. Substituting for $\lambda_g$ and $\lambda_d$, and rewriting, we have:

$$\tau_g \dot{P}_g = \lambda - b_g - c_g P_g$$

$$\tau_d \dot{P}_d = b_d + c_d P_d - \lambda$$

$$P_g = P_d$$

This forms a system of equations which can solved. One can find the stability point of the market by setting the time derivatives to zero and solving. One gets the following for the one supplier, one consumer case:

$$P_g = \frac{b_d - b_g}{c_g - c_d}$$

$$P_g = P_d$$

$$\lambda = \frac{-b_g c_d + c_g b_d}{c_g - c_d}$$

Thus, this market has an equilibrium point and the power in the system and the market price at that equilibrium point can be computed. Note that there is one, and only one, equilibrium point.

Power levels in the real world are anything but constant. One might ask whether the system remains stable away from the equilibrium level. Also, there is no discussion of how supply and demand are forced to be in balance. A dynamic simulation of the model can help answer these questions.

## 3 Simulation in MATLAB using SIMULINK

### *3.a. General*

In order to simulate this simple market model, the SIMULINK GUI-based simulation package in MATLAB was used. SIMULINK is nice for simulating simple systems because the graphical interface is basically point-and-click, it is easy to plot any variable in the system or relationships between variables, and one has a visual image of their system right in front of them.

Representing the block simulating the generator's reaction to market price is shown in Figure 1. The block for the consumer is the same except for different constants and a sign change.

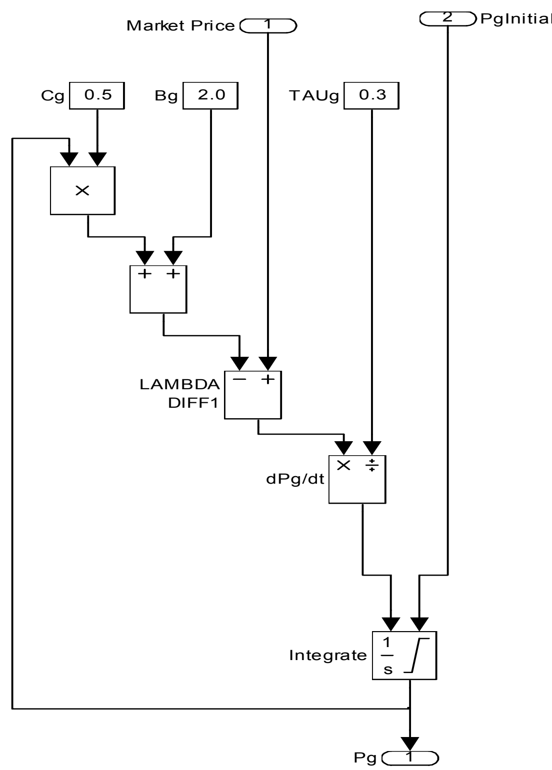


**Figure 1 Block diagram of generator response to price.**

### *3.b. Pricing rules with immediate feedback*

To actually run a simulation, one needs a relationship between the actions of the market participants and the market price, that is to say, a pricing mechanism. Alvarado [1] doesn't specify such a relationship in his paper, nor does he need to for what he does; but we need one here. An issue of considerable interest in the electrical industry is how the market price should be determined. An auction method uses some sort of bidding system, but in this simple model there is no provision for bidding. Therefore, the market price must be set using the market participants' actions. An initial pricing model is one in which price goes up when the amount of power demanded by consumers is greater than the power being generated by the suppliers. The simplest case would be if the relationship were linear, i.e.,

$$\dot{\lambda} = k * (P_d - P_g)$$

where k is a proportionality constant. This is an attempt to model the effect on price when supply and demand are not in balance and is the mechanism whereby they are brought back into balance. This requires that the change to the price be calculated in real time and fed back to the market participants. In practice, ancillary services might have to be used to insure short-term power stability and quality. Such a model appears in Figure 2, which shows change in market price being proportional to the power difference and being fed back to the participants. Note that initial values for $P_g$, $P_d$, and $\lambda$ (labeled "LAMBDA" in the diagrams) can be entered. Running the simulation will show how the system evolves from those initial conditions. Initially, values for the equilibrium point may be entered(using the case given in Alvarado [1] where for the generator $b_g$=2.0, $c_g$=0.5, $TAU_g$=0.3, and for the consumer $b_d$=10.0, $c_d$=-0.5, $TAU_d$=0.2) and verify that the equilibrium point is stable. When this was done the system remained at the equilibrium point with a power level $P_g$=$P_d$=8.0 and market price LAMBDA=6.0.

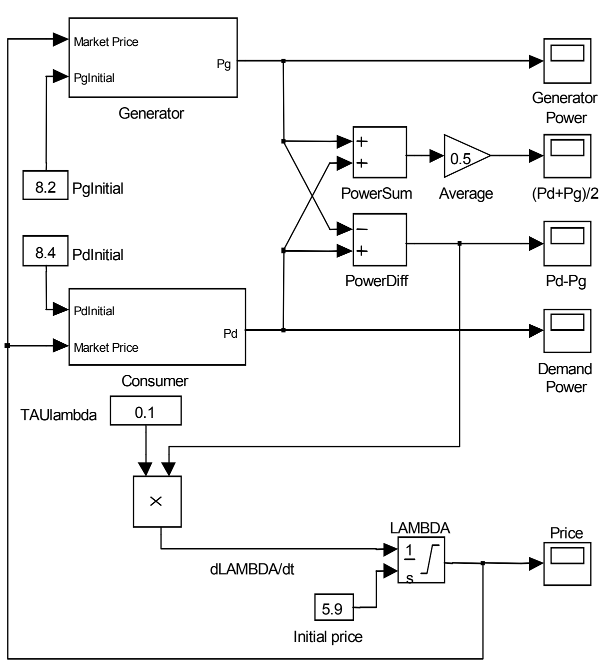


**Figure 2 Full model of the market, showing immediate feedback of market information.**

But what happens when the system strays from this equilibrium point? If the system is perturbed slightly, by choosing initial values slightly away from the equilibrium level, is the system stable? For initial values of $P_g$=8.2, $P_d$=8.4 and LAMBDA=5.9, the system returns to the equilibrium level as shown by Figures 3, 4, and 5. This may be considered undesirable since the system did not remain at the initial values or since the final power level was not somewhere between the initial levels of the producer and consumer. It can be argued that this is unrealistic because power levels constantly change as demand increases (e.g., people wake up in the morning and turn on their coffee pots and hair dryers). But this a simple model and simple models often have simple behaviors. In this model, consumption is not dependent on sleep patterns, hunger, or social vanity; consumers react only to market price.

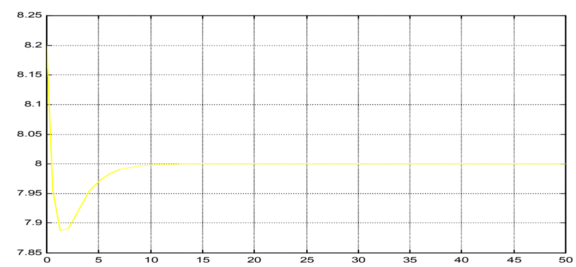

**Figure 3 Generated power with immediate feedback.**

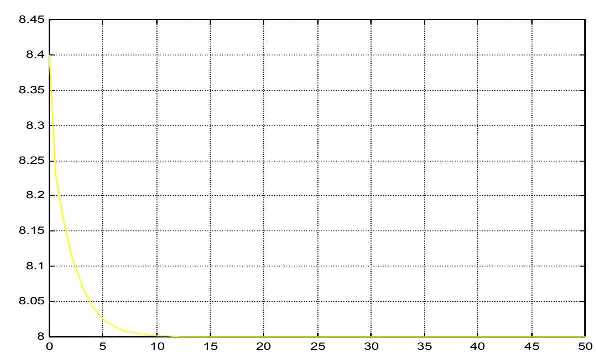

**Figure 4 Demanded power with immediate feedback.**

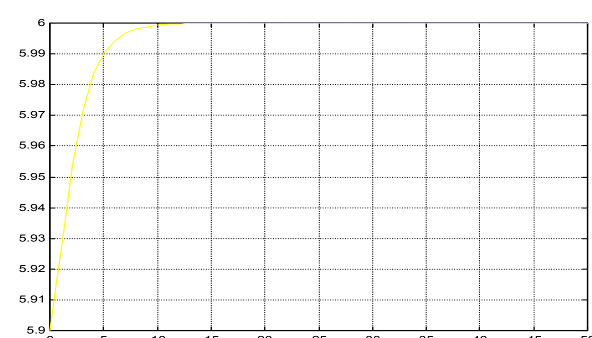

**Figure 5 Market price with immediate feedback.**

### *3.c. Pricing rules with delayed feedback*

In the example above, the price was proportional to the difference between demand and supply and this information was immediately available to the supplier and consumer. In other words, the market participants' had immediate feedback as to the consequences of their actions. In the real world, there might be a delay in this process induced by any number of administrative or practical constraints. With a simulation like the one here it is easy to delay the feedback mechanism. This is done by adding a unit delay in the line where the change in price is added to the price (see Figure 6). When the model is run with this delay in place, starting away from the equilibrium point as before, the system again returns to equilibrium level but it overshoots the point before settling down (see Figures 7, 8, and 9). Where the system seems to exhibit over-damped behavior with instantaneous feedback, delayed feedback results in an under-damped behavior.

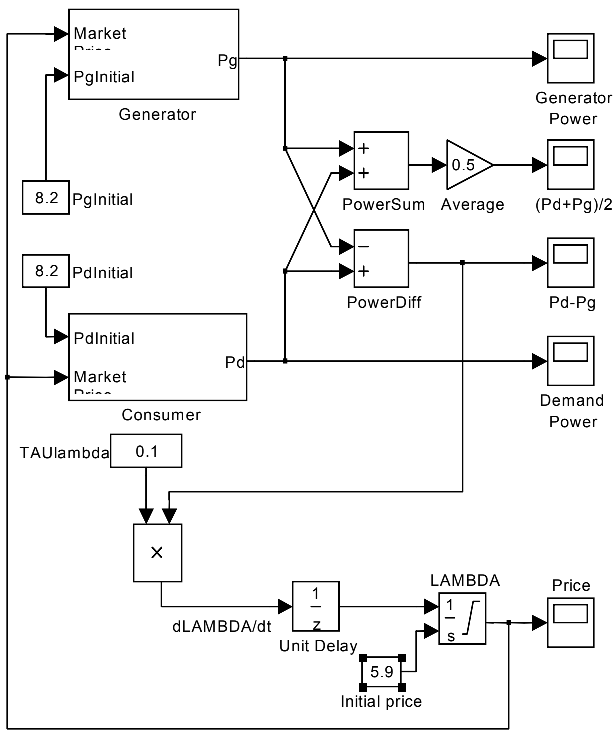


**Figure 6 Diagram of model with a delayed updating of the market price.**

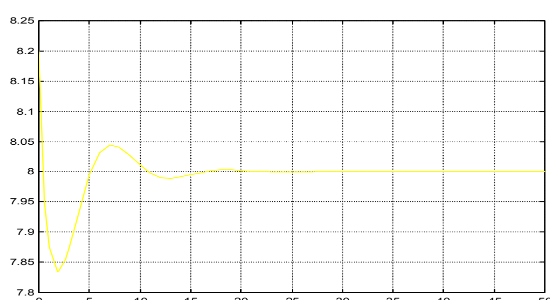

**Figure 7 Generated power with delayed feedback.**

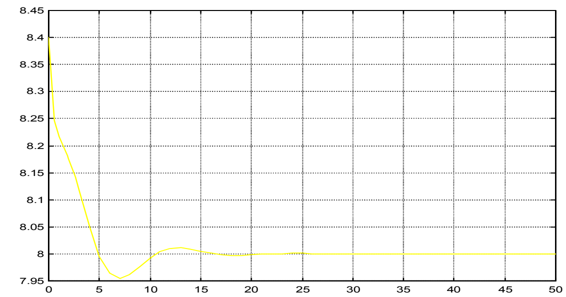

**Figure 8 Demand power with delayed feedback.**

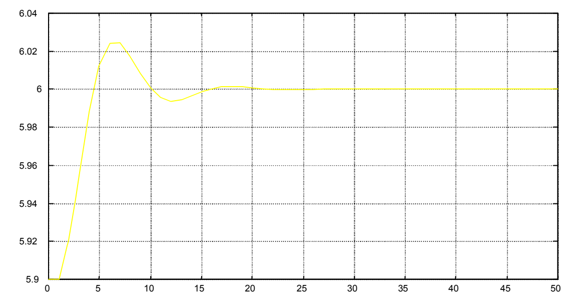

**Figure 9 Market price with delayed feedback.**

## 4 Observations

This simple model with a producer and a consumer whose market behavior is determined by the market price and their marginal cost/benefit has only one equilibrium point and the system eventually find itself there. In a real market, power levels are known to fluctuate.

The way in which the system returns to the equilibrium level is dependent upon whether feedback from the market of the effects of the market participants' reaction is immediate or delayed.

Modeling market participant actions as a blind response to price levels is unrealistic. These behaviors would be forced to change due to predation by more flexible market participants.

The interplay between the pricing mechanism and the market participants' behavior must taken into account when determining the behavior of the system

## 5 Agent-Based Computational Economics

We have seen that classical control theory predicts a stable market given agents who react to the market according to some programmed behavior and who do not swerve from that program. We have also seen that the dynamics of this "stable" market may not necessarily be stable or well-behaved. The pricing mechanism chosen for the simulation here resulted in rather egregious oscillations of both electrical power and market price. Any investigation of the stability of a competitive electricity market must specify the pricing mechanism being used and any other market information being fed back to the market participants.

We now turn our attention to the market participants: while it is convenient to assume simple responses of the suppliers and consumers to price levels and that these responses don't change over time, these assumptions are, at best, a simplification of reality and, at worst, misleading. The fact is that the players in power markets are not static, their responses to market conditions can be very complex, and they can modify their behavior as time goes along, varying their strategies to optimize their position.

It is difficult to see how such a complex system can be reduced to equations in such a way that it can be suitably handled by control theory. And even if one can write down a system of equations that accounts for the majority of what is really happening, the chances that it will have a useful closed-form mathematical solution are slim.

Needed is a way to model each part of these complex systems without having to make possibly unrealistic assumptions in order to insure that a solution to the model can be found. This research proposes agent-based computational economics (ACE) as a way to approach the design and simulation of complex power markets. As suggested by its name, ACE uses interacting agents to do economic computations. There are a number of reasons why agents are well suited to economic problems. The first, and perhaps most obvious, reason is that an economy is essentially a collection of participants each acting in their own way, hence in the model each player can be modeled independently. Secondly, the agents can be allowed to interact in myriad ways, without those interactions being constrained by the necessity of formulating them as a set of equations. Thirdly, the agents' behavior need not be modeled as a differentiable function; it can be discontinuous and non-differentiable if that is what best models the system of interest. By using agents, research can concentrate on modeling each part of the system as accurately as possible without being hindered by the notational complexity and mathematical requirements of differential linear algebra. The benefit of using the many tools and techniques of traditional control theory for analyzing the system of equations describing the system may be lost, but the power and flexibility afforded by agent-based systems makes an ACE approach very worthwhile.

In order to answer some of the questions raised in the replication of Alvarado's results, the intent is to use agents to simulate 1) the market participants and 2) the pricing mechanism. The agents will be adaptable, meaning that their behavior is modified over time. Rather than react blindly to price, using the same strategy forever, they will be able to select which information is most important to them and adapt their behavior to act on that information. Part of the limitations of algebraic problem solving is that the behavior of the system, i.e. the market participants' reactions and the feedback mechanisms in the market, must be specified in advance. While this is useful to investigate specific scenarios, it doesn't necessarily lend itself to finding optimal market structures and optimal behaviors in those markets.

With the coming of the computer revolution, analysis techniques and simulation methods have become possible of which previous researchers could only dream. Rather than spending a lot of time and great effort constructing a set of equations and trying to find closed form solutions which describe the behavior of the system, one can now simulate literally thousands of possible systems and classify their behavior. For the first time it is possible to search for an optimal function or system of functions rather than trying to optimize a contrived system.

With an agent-based simulation running on today's fast computer processors, researchers can explore the space of markets. Just as one can search for the maximum of a function such as the distribution of an electric field in real space, so one can also search for an optimal market configuration in market space. This is essentially what we will do with our agent-based market simulation. The authors will test different market structures and allow the agents interacting in those markets to adapt their strategies.

The research will begin with a two pronged attack: either setting the market configuration to be static (e.g. the pricing mechanism) and then evolving agents within that market, or freezing the agent behavior and allowing the market structure to adapt. The reason for separating these, at least initially, is to address each question independently. In the deregulation of the electric power industry, there are two camps: the regulators and the regulatees. The regulators want to insure reliability of the electric power system, quality of power, open access to transmission, and fair pricing. The regulatees, i.e. the producers, consumers, transporters, resellers, etc., want to know how to maximize their profit, minimize their risk, and not be taken on a roller-coaster ride in the process. For this reason it is best to begin by separating the two and investigate each separately. From a practical viewpoint, this is also the best way to deal with existing or planned markets and find out what their dynamics are. From a theoretical view point, one might want to allow both the market structure and the agents within the market to evolve together in order to find the system of regulatory rules and operating strategies which result in the optimal electrical market.

This is a daunting task and the number of different scenarios and options is almost limitless. Starting with the simple model presented above with producers and consumers interacting via a simple pricing mechanism, one quickly begins to think of things to add and different things to try. This is where the flexibility of a modularized approach like an agent-based system shows its true value to the researcher. It is easy to add pieces and test the result. The modular design makes it possible to add modeling for a futures market and have agents that can use it to maximize their profit/utility function. Trying to formulate a futures market and its interaction with the spot market using linear algebra would be difficult if not impossible.

## 6 Complex Agent Behavior through GP-Automata

### *6.a Evolving Agents*

There are many different ways of programming adaptive agents as shown by a quick look through the current literature. There are neural networks, genetic algorithms, and others. Neural networks (NN) are nice for problems in which can be reduced to finding an optimal function for some task. They are well suited for problems in which the search space is relatively smooth there are no localized sub-optimal solutions. Genetic algorithms (GA) are another search mechanism in which the parts of the problem are coded as a "gene" and one searches for the best collection of genes. They are less susceptible to being trapped in localized sub-optima than are neural nets because one normally tests an entire population of genes all at the same time, which essentially examines discrete points in the search space and selects those grouping of genes that best solve the problem. The basic genetic algorithm can be written as follows:

1. Randomly initialize a population and set the generation counter to zero.
2. Until done or out of time, do the following:
   - Calculate the fitness of each member of the population.
   - Select parents using some fitness bias.
   - Crossover the parents to create candidate offspring.
   - Mutate these new offspring.
   - Replace the lesser fit members with the offspring.
   - Increment the generation counter and go to step 2.

The authors have had some success in previous research in using GAs for constructing adaptive agents. For our simulation of electrical markets we plan to explore the use of GP-Automata. GP-Automata combine genetic programming (GP) and finite state automata. This technique allows complex strategies to be evolved.

### *6.b The Basics of Genetic Programming*

The process of genetic programming has been called automatic programming and is a sub-class of the genetic algorithm field. Genetic programming is a fairly new discipline and is attributed to John Koza [5]. Typically shown in either parse tree (see Figure 10.), or S-expression form (e.g.: avg( ite( sub( hbb, cost), 20, asb), 10)). Genetic programs (GPs) are evolvable programs. Each parse tree contains some number of nodes and branches. The branches connect the various nodes which can be either an *operational node* which has arguments and performs some operation involving those arguments, or *a terminal node*.

The designer specifies the set of valid operators and terminals suitable to the problem being investigated. In designing GPs for the GP-Automata, it is desirable to give the trees an opportunity to return numbers in the range of competitive bids, if presented with a bidding problem.

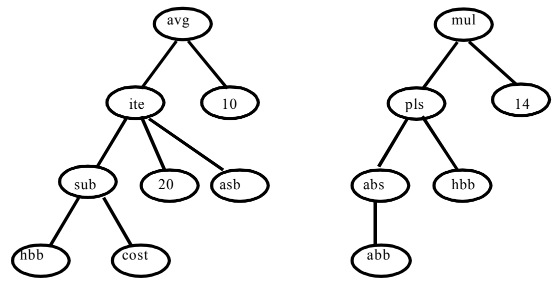


**Figure 10. Sample GPs.**

Valid GP trees are initialized randomly and then evolved in a standard genetic algorithm (as described in the previous section) with the following modifications. Crossing over two parents involves randomly selecting a node from each parent and swapping the sub-trees rooted at those nodes. *Mutation* involves randomly selecting a node in the candidate child and throwing away its sub-tree. In its place a new sub-tree is generated randomly. The GP field is new and quite complex at first glance; please see Koza [5,6] for more details.

### *6.c GP-Automata*

GP-Automata combine finite state automata with GP. They were first described as such by Ashlock [3]. The typical finite state automaton specifies an action and "next state" transition for a given input or inputs. Encoding complex agent strategies or behaviors into a finite state machine can be somewhat involved. The number of transitions needed to account for all possible for behaviors and input combinations grows exponentially. This is where genetic programming comes in. The GP-trees perform bandwidth compression for the GP-Automata by selecting which inputs to consider and performing computations involving these inputs. See Fig. 11 for an example of a GP-Automaton used to generate bids for an auction.. Reading the rule encoded by the GP-Automaton in Figure 11 is fairly simple. We see that this automaton begins by bidding the number in the 'initial action' field. Following the initial action, the 'initial state' tells us which state we would use next (in this case, 2). The GP-Automaton in the figure has four states. Coupled with each of these states is a GP-tree termed a decider. When executed, the decider returns a value between 0-100. Based on that returned value, one of the following two things will happen. (a) If that value is *even* after truncation, the action listed under 'IF EVEN' is taken and we move to the next state listed under 'IF EVEN'. (b) If the returned value is *odd* after truncation, then we use the action and next state listed under 'IF ODD'. The 'action' is the number listed in the action field of the automaton, with two exceptions. The first exception is the ‘U’ which indicates that the value returned by the decider should be taken directly as the action. The second exception is a ‘*’ which indicates that further computation is necessary and hence the GP-Automata refrains from acting immediately. Instead, it immediately moves to the next state. This gives rise to the possibility of complex (multi-state) computation as well as infinite loops. To prevent infinite loops, after an externally specified maximum number of ‘*’s, an action is selected at random from actions uniformly distributed over the valid range.

| | IF ODD | | IF EVEN | | |
|---|---|---|---|---|---|
| State | Action | Next State | Action | Next State | GP (Decider) |
| 1 | 14.5 | 1 | U | 1 | lte (mul (10, abs ( hbb ) ) |
| 2 | * | 1 | 37 | 3 | ite (max(10, asb),hbb,lbb) |
| 3 | 12 | 2 | 5 | 1 | Avg (5, abb) |
| 4 | U | 3 | * | 2 | 47 |
| Initial Action | | 24 | Initial State | | 2 |

**Figure 11. A four state GP-Automaton that generates bids.**

The power of GP-Automata lies in their abililty to deal with complex problems with multiple inputs and reacting differently depending on their state. Of particular value to the research who evolves a population of GP-Automata to solve some task is the the rules and calculations are easy to read and can be interpreted (unlike a neural network whose collections of thresholds and connection weights jealously guard the secret of the meaning held within). The “program” in the GP-Automata can be read by a human expert, which can supply them with insight into the finer points of the solution or be used to discard solutions which have high fitness but in actual fact are using a trivial or static strategy.

## 7 Summary and Future Research

A simple model of electricity markets in which market participants actions are dependent only on their cost and benefit curves can be useful for making tests as to the possibility of stability of those markets. They allow one to investigate questions such as what type of pricing mechanism can be employed should be employed and the effect of information delay on the market stability

Ultimately, these simple models will need to be extended to allow for market participants whose behavior changes. The deregulated electricity markets forming around the world are going to be populated with complex agents with diverse agendas and ways of operating, each trying to maximize their profit, gain market share, and be successful. These complex markets and behaviors will require more complex and extensible models. The GP-Automata is an excellent way to model adaptable systems. Our future work will be to evolve market agents and market structure and investigate optimal bidding strategies and discover stable market structures.

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## 10. Biographies

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