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Swarm Engineering for Agent-Based Economics

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Abstract— **The *Hamiltonian Method of Swarm Design* is applied to the design of an agent based economic system. The method allows the design of a system from the global behaviors to the agent behaviors, with a guarantee that once certain derived agent-level conditions are satisfied, the system behavior becomes the desired behavior. Conditions which must be satisfied by consumer agents in order to bring forth the "invisible hand of the market" [18] are derived and demonstrated in simulation. A discussion of how this method might be extended to other economic systems and non-economic systems is presented.**

Keywords: swarm engineering, Hamiltonian method of swarm design, swarm economics

1 Introduction

Complex system design is a challenging field of science in which some to many independent interacting parts are combined so as to create a machine or system with a particular desired function or property set. A subset of the general field of complex systems is swarms, which are groups of bidirectionally communicating autonomous agents. Swarms are interesting for a number of reasons, the most important of which is the tendency of swarms to exhibit *emergence*, which allows them to undertake actions that are not explicitly part of the control algorithm.

The most challenging thing in complex system design is ensuring that the different parts will interact with each other in a such a way as to generate a desired system behavior. This is particularly true for systems of autonomous agents. Since each agent is independent, the interactions can be very difficult to predict, *a priori*.

In the swarm literature, there is little in the way of generally applicable principalled approach to swarm design. Some researchers [21, 17] have built preliminary systems for monitoring or understanding the emergent behaviors of agents. However, these studies do not yet generalize to a methodology that works for a large number of swarm systems. As a result, no particular method exists for generating swarms of particular design.

In this paper, we examine what we call the ***Hamiltonian Method of Swarm Design (HMOSD)***[6]. This method is a principalled approach to swarm design consisting of two main phases. In the first phase, the global goal(s) is(are) written in terms of properties that can be sensed and affected by the agents. The resulting equation(s) can then be used to develop requirements for the behaviors of the agents that lead to the global goal.

Though swarm engineering has typically been applied to robotic design and computation design, we broaden the scope here by applying it to an economic system. So why economics? Economies are complex systems which encompass micro and macro behaviors, individual interaction, equilibriums, and, in most cases, some sense of self-regulation [17]. Because of this overwhelming complexity, a quantitative form of economics has been difficult to observe. However, with more powerful computational power and the development of efficient control algorithms it is now possible to approach economics from a more quantitative, rather than theoretical, perspective [4][5][11]. One such control method is swarm engineering. Just as a real economy is decentralized, automated swarms require no outside control [6]. An accurate simulation can be run solely by itself, basic economics laws and theories governing the physics of interaction of agents. An advantage of this method is the lack of the ceteris paribus (Latin for "all other things unchanged") aspect of traditional economics. Observations qualified by ceteris paribus require that all other variables in a causal relationship are ruled out in order to simplify studies. A swarm controlled simulation, on the other hand, allows all factors to be included in the relationship between antecedent and consequent [6][7]. Another salient advantage is an observer's ability to control the basic structure of interaction. Before a run, the simulation allows one to tinker with basic parameters of the system, such as sizes of budgets, rate of utility increase, and the magnitude of competition. By allowing such control, a user can predict results of economies in several types of real-life situations, which is key in understanding the scope of economic systems and the realistic range of our control.

Real economic systems are systems of autonomous agents with bidirectional communication, satisfying a broad definition of a swarm. Thus, it stands to reason that swarm engineering techniques might be able to be applied to such a system so as to generate a predefined global behavior of the system. Many studies have been made which use agent-based simulations in which inter-

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actions between agents define what the economy will do [1, 4, 8, 10, 11, 12, 15, 16, 19]. However, though these studies extracted global behaviors from their systems, they did not develop or apply a method of generating the global behavior, and then designing the system around that behavior. This study, which might be termed a study in *swarm economics*, is meant to examine the design phase of an economic system using the swarm engineering methodology.

The remainder of the paper is organized as follows. Section 2 examines the theoretical application of the HMOSD to a simple economic model. This section focuses on the properties of the agents that will give the economy a particular behavior. Section 3 presents the performance of the model under different expected agent behaviors. Section 4 offers some discussion and concluding remarks.

2 Swarm Engineering Applied to Economic Systems

In this section, we will theoretically explore the application of the principles of swarm engineering to economic systems. In swarm engineering, we are primarily interested in generating group behaviors by utilizing careful examination of the desired global behavior and using this analysis to guide the design of agent-level behaviors capable of producing the desired global behavior [6]. While this method still requires considerable input from the engineer, we have been able to use it to solve previously unsolved problems in deployment of swarms. In the present study, this means that we are interested in examining one or more global economic measurables and putting together a method of directly manipulating these by designing specific agent behaviors.

In economic systems, there are many global measurables. Each one is tied to local variables in a complicated and non-linear way. This makes the prediction of the global effect of a specific local behavior very difficult. As a result, it is often times simpler to utilize agent-based systems to get an idea of the effect of specific behaviors. The difficulty with utilizing agent-based systems in this way derives from the difficulty in creating a new system with specific desired qualities; the nonlinearity of complex systems makes this a very difficult thing to do. As a result, we utilize the swarm engineering methodology, which draws its initial motivation from the desired global outcome.

As our global property, we choose a truly dispersed property – that of the average cost of a commodity across vendors for sales of specific commodities. This property is interesting because it measures how much a consumer pays for goods and services that are worth a specific amount. If all vendors tend to end up with similar prices, this indicates that either the system is designed to enforce a specific price, or that there is some kind of communication between vendors that allows them to collude. We shall see that there are specific system designs that allow the former to occur without collusion or any communication between vendors.

We examine the design of consumer behavior as a method of controlling the average price. Vendors are modelled as profit maximizers who will increase their prices when all else is kept constant. The reaction of the consumers must be made in such a way that slow creeping price increase does not occur. We shall see that specific agent behaviors, designed properly, can limit the average prices to prices that very closely match the cost of vending the product.

2.1 Vendors and consumers

We begin by modelling the main factors that affect the vendors in their decision to alter prices of commodities that they are selling. We begin with the assumption that all vendors will choose a price for a commodity that equals or exceeds his or her costs incurred during the sale of the commodity. The question then is what factors affect the change in the price?

We begin by assuming that the price function used by a vendor is a complicated function of several different values. That is, let the price be represented as

$$p_{v,c} = f(m_1, m_2, \ldots, m_n). \quad (1)$$

Then, each of these values m_i represents a factor in determining the price of the commodity.

There are many factors one might include in a decision about the cost of a commodity or in a decision about whether or not to increase the cost of a commodity. Among these factors are the demand for the commodity (D), the vendor's account balance (b), the total cost of the commodity to the vendor including the cost to put it on the shelf (space, cost outlays, and personnel) (c_c), any memorized or recorded data of the past l cycles ($\{m_j\}_{j=1}^{l}$), and the current income of the vendor (i). We assume, for the moment, that these are the main effectors of the cost of the commodity.

As we stated above, our goal is to examine the dynamics of the average price of specific commodities. This is the average price over all vendors of the commodity. I.e.,

$$P_{a,c} = \frac{1}{N_v} \sum_{v=1}^{N_v} p_{v,c} \quad (2)$$

where $P_{a,c}$ is the average price for commodity c, N_v is the number of vendors, and $p_{v,c}$ is vendor v's price for the commodity c.

In real economic systems, the average price of a specific commodity typically remains stable or increases over time. However, theoretical prices should actually decrease or remain stable over time as the cost of production decreases. Moreover, the market is assumed to produce corrections to initially poorly priced items (i.e. items whose prices are much higher than the cost to produce it). We are interested in discovering what the minimal conditions are for consumers which will result in commodity prices that decrease or stabilize over time. This can be written mathematically as

$$\frac{dP_{a,c}}{dt} = \frac{1}{N_v}\sum_{i=1}^{N_v} \frac{dp_{v,c}}{dt} \leq 0. \tag{3}$$

If a single vendor's prices start decreasing, then under competitive conditions, all vendors' prices should start decreasing. This being the case, we don't expect one vendor's price to increase while any of the other vendors' prices decrease. As a result, we can replace the requirement of (3) with

$$\frac{dp_{v,c}}{dt} \leq 0. \tag{4}$$

If we begin by assuming that the vendors have a systematic method to their pricing choices, then we may write the prices faced by consumers as (1). Utilizing the various measurements indicated above, this means that

$$\frac{dp_{v,c}}{dt} = \frac{\partial f}{\partial D}\frac{dD}{dt} + \frac{\partial f}{\partial b}\frac{db}{dt} + \frac{\partial f}{\partial c_c}\frac{dc_c}{dt} + \sum_{j=1}^{l}\frac{\partial f}{\partial m_j}\frac{dm_j}{dt} + \frac{\partial f}{\partial i}\frac{di}{dt}. \tag{5}$$

The term in (5) $\frac{\partial f}{\partial c_c}\frac{dc_c}{dt}$ would seem to have little to do with the consumers, and so cannot be directly affected by a behavioral change among consumers. We therefore ignore it as a potential design point. On the other hand, it is interesting to note that $\frac{db}{dt}$ is the rate at which the bank account changes. Thus, we identify this with the profit. If profit is Pr then,

$$Pr(t) = \frac{db}{dt} = D(t)\left(f(t) - c_c(t)\right). \tag{6}$$

where $D(t)$ represents the number sold per time period. Moreover, this profit/loss may be memorized by the agent, affecting behavior. For each vending agent, the behavior can be different, but in general

$$m_k(t) = Pr(t - kt_p) = D(t - kt_p)\left(f(t - kt_p) - c_c(t - kt_p)\right) \tag{7}$$

where t_p represents a time period and k represents the specific memory element being stored. k typically runs from 1 through N_m, the number of memory elements used in the function.

Since we are examining conditions that make $\frac{dp_{v,c}}{dt}$ a non-increasing function of time in the absence of inflation and supply variations, we want

$$0 \geq \frac{\partial f}{\partial D}\frac{dD}{dt} + \frac{\partial f}{\partial b}\frac{db}{dt} + \frac{\partial f}{\partial c_c}\frac{dc_c}{dt} + \frac{\partial f}{\partial m_{p/l}}\frac{dm_{p/l}}{dt} + \frac{\partial f}{\partial i}\frac{di}{dt}. \tag{8}$$

As a result, we have that

$$\frac{\partial f}{\partial D}\frac{dD}{dt} \leq -\left(\frac{\partial f}{\partial b}\frac{db}{dt} + \frac{\partial f}{\partial c_c}\frac{dc_c}{dt} + \frac{\partial f}{\partial m_{p/l}}\frac{dm_{p/l}}{dt} + \frac{\partial f}{\partial i}\frac{di}{dt}\right) \tag{9}$$

Inserting the results of (6) and (7) reveals that the actual form of this equation becomes

$$\frac{\partial f}{\partial D}\frac{dD}{dt} \leq -\left(\frac{\partial f}{\partial b}\left(D(t)\left(f(t) - c_c(t)\right)\right) + \frac{\partial f}{\partial c_c}\frac{dc_c}{dt} + \frac{\partial f}{\partial i}\frac{di}{dt}\right) - \left(\sum_k \left[\frac{\partial f}{\partial m_{p/l}} D(t - kt_p)\left(f(t - kt_p) - c_c(t - kt_p)\right)\right]\right) \tag{10}$$

In the case that the vendor simply reacts to current conditions, the relation takes the form

$$\frac{\partial f}{\partial D}\frac{dD}{dt} \leq -\left(\frac{\partial f}{\partial b}\left(D(t)\left(f(t) - c_c(t)\right)\right) + \frac{\partial f}{\partial c_c}\frac{dc_c}{dt} + \frac{\partial f}{\partial i}\frac{di}{dt}\right). \tag{11}$$

Now, we examine (10) to determine the form of f.

1. If the cost to the vendor increases, it is reasonable to expect the vendor to either increase or hold steady its prices. That is

$$\frac{dc_c}{dt} > 0 \Rightarrow \frac{\partial f}{\partial c_c} > 0. \tag{12}$$

2. If the income increases, one can infer that the demand at a particular price has increased. Therefore, by increasing the price, the profit will increase. Thus, we expect that

$$\frac{\partial f}{\partial i} > 0. \tag{13}$$

3. If profit increases, one can infer that the demand at a particular price has increased. Therefore, by increasing the price, the profit will increase. Thus, we expect that

$$\frac{\partial f}{\partial b} > 0.$$

4. If the demand increases, typically the price increases. Therefore we expect that

$$\frac{\partial f}{\partial D} > 0$$

These results together give us that

$$\frac{dD}{dt} \leq -\frac{1}{\frac{\partial f}{\partial D}}\left(\frac{\partial f}{\partial b}\left(D(t)\left(f(t) - c_c(t)\right)\right) + \frac{\partial f}{\partial c_c}\frac{dc_c}{dt} + \frac{\partial f}{\partial i}\frac{di}{dt}\right) - \left(\sum_k \left[\frac{\partial f}{\partial m_{p/l}} D(t - kt_p)\left(f(t - kt_p) - c_c(t - kt_p)\right)\right]\right) \tag{14}$$

or in the case that the agents are purely reactive

$$\frac{dD}{dt} \le -\frac{1}{\frac{\partial f}{\partial D}} \left(\frac{\partial f}{\partial b} \left(D(t) \left(f(t) - c_c(t) \right) \right) + \frac{\partial f}{\partial c_c} \frac{dc_c}{dt} + \frac{\partial f}{\partial i} \frac{di}{dt} \right). \tag{15}$$

We have just proved the following theorem.

Theorem 2.1 *If the condition in equations (14) or (15) continually holds, then the price will be bounded above.*

These last two equations give the limits of the behavior of the consumer agents in a system composed of the vendor and consumer agents only. It indicates that the consumer agents must respond with a decrease in the demand for a commodity which is greater in magnitude than the magnitude of the right hand side of equations (14) and (15). This is a severe design requirement on the consumer agents. However, as we will see in the next section, systems containing consumer agents which follow these restrictions do tend to have the desired global characteristics, while those that do not tend to have significantly higher to run-away prices.

2.2 Design of consumer agents

Our primary concern is that the consumer agents provably behave in such a way that the global average price remains bounded above. We have already seen in section 2.1 that if the conditions in equations (14) and (15) are obeyed, the goal will be achieved. That completes the top-down portion of the design problem. We now have an engineering requirement with which to work. We can now begin the bottom-up phase.

In this new phase, we must generate agents that satisfy this requirement. The general solution to the general equation given in (15) if $\frac{\partial f}{\partial i} = \frac{dc_c}{dt} = 0$, $\frac{\partial f}{\partial D} = \alpha, and \frac{\partial f}{\partial b} = \gamma$, the general solution is

$$D = e^{-\int_0^t -\frac{\gamma}{\alpha}\left(f(t') - c_c(t')\right)dt'}. \tag{16}$$

As a result of this general solution, it is clearly the case that, in order to react correctly in the next time frame, our agents must have the following capabilities.

1. The agents must be able to measure the price of the commodity.
2. The agents must be able to measure the demand for the commodity. In our simulations, it is a good estimate to know one's own probability of purchasing the commodity and multiplying by the population size.
3. The agents must be able to accurately estimate the cost to the vendor.

Thus, all agents must have this capability, and their behavior must be one of this family of behaviors. We can write this as an update rule. This becomes

$$D_{i+1} = D_i \left(1 - \frac{\gamma}{\alpha} \left(f_i - c_{c_i} \right) \right). \tag{17}$$

This equation underscores the idea that the demand will remain constant when the price is near the cost. However, as the vendors will constantly be trying to increase the price, and the consumers will be reacting to increases, the actual average price will be greater than the cost to vendors. It is worth noting, of course, that in the real world, this cost is replaced by a very poorly defined notion of the "value" of an object. Since consumers have no idea, in general, how much a specific object actually costs in real terms, they must guess about it's value. However, despite this ignorance-driven inflation, the prices, once equilibrated, must respond to the same type of force.

In the next section, we describe our simulation and the behaviors of the agents carrying out repeated cycles of interactions between consumers and vendors. We generate a family of behaviors parametrized by a small number of parameters. Some values of the parameters generate behaviors that obey the requirements of (15) and some do not. We explore the effects of these parameters and demonstrate that they yield the expected global behaviors.

3 Simulation Design

We examine our theoretical results using a computer simulation that centers around the interactions between two types of agents: consumers and vendors. Our simulation functions by creating repeated interactions between the consumers and vendors as they learn and react to certain situations [19]. Vendors have commodities to sell, and are designed to maximize profit. Consumers purchase commodities from vendors using money provided to them by jobs, and attempt to maximize consumption. The simulation proceeds by repeated "sessions" during which consumers visit vendors, evaluate what the vendors have to offer, and decide whether or not to buy. Vendors respond to changes in their products' marketability by changing prices in an attempt to increase their profit.

In our simulation, many details come into play. Both consumers and vendors have memory which help them decide on things such as which of the other class of agents to do business with, how to change prices, etc., and how to respond to current offerings [10]. In the coming subsections, we explain these in detail, including motivating assumptions borrowed from economic theory. Our goal is to test our method of designing agents whose interactions produce a desired global goal, namely the control of the average price of a commodity. We describe, in addition to the agents' designs, the tools used to evaluate the function of the system.

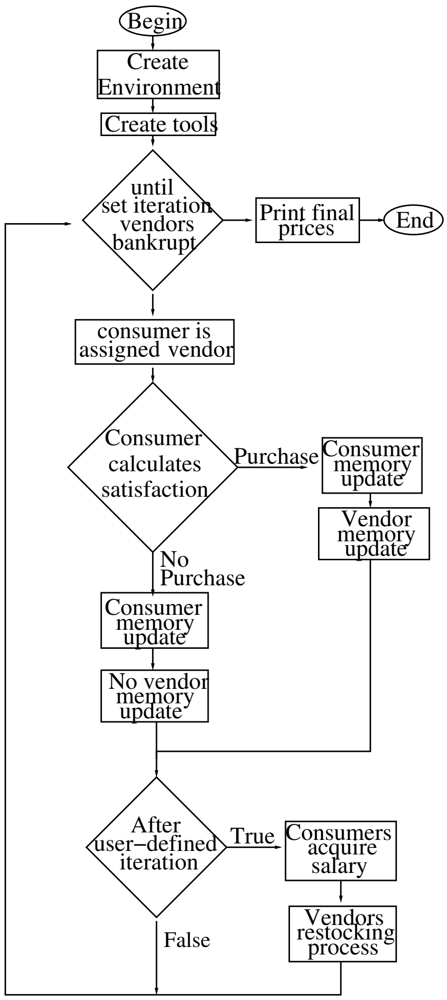

Figure 3.1: This is a general flowchart of ABES

3.1 Vendors

As soon as ABES is executed, the products are assigned a random cost. Each vendor sells a single commodity, and so must assign and manage the price of the single commodity. Each vendor calculates its own minimum price. Initially, the price is set at twice the cost to the vendor. All the profits made from a completed exchange is directly added to the vendor's bank account, the total amount of money that the vendor has. The vendor will restock its inventory when the number of products it holds reaches a user defined number if there is enough money in the bank to purchase more products. If the vendor fails to restock using the amount of money in the bank, then that vendor is considered bankrupt and is removed from the pool of vendors. As a result, the bankrupt vendor no longer participates in the interactions between vendors any consumer.

Each vendor's goal is to maximize its profit by any means. After a user-defined number of iterations, if the vendor has made more profit than it did in the previous period, the prices of the vendor's product are incremented by a constant, user defined percentage of the product's cost. This price update rule comes from the assumption that vendors will expect the same number (or nearly the same number) of products to sell the next period. A slight increase of price will increase the total profit. Conversely, if the vendor has made less profit, it reduces its prices by the same percentage. This behavior of decreasing the price derives from the assumption that the vendor will sell more the next period by slightly decreasing the price. This should increase the total profit.

3.2 Consumers

Behaviors of our consumers are similar to consumers in [16]. Each consumer interacts with its vendor in the same way: the consumer buys from the vendor if all of the conditions are met each time the consumer randomly chooses a vendor to buy the commodity from. We assume the commodity is something the consumer eventually must buy, like water. If the consumer waits long enough, it will be forced by necessity to purchase the commodity at any price. If the consumer has enough money, the item is in stock, the vendor is not bankrupt, and the consumer is "satisfied" with the product, the consumer will purchase the product. The consumer's satisfaction with the vendor's products is represented by a number from 0 to 100, and is affected by the length of time since the last purchase, the consumer's memory of the prices, and the vendor's profit margin. Along with the information in the consumer's memory, the consumer calculates its satisfaction toward the product. A random number from 0 to 100 is generated, and if the calculated satisfaction is higher than the generated number, then the consumer will be considered "satisfied" enough to buy the product. Thus, the higher the satisfaction of the consumer is, the more likely the consumer is to purchase an item from the vendor. Each consumer's cache of money is incremented by a user defined salary after some number of iterations, and decremented by the amount of each purchase.

The goal of the consumer in our simulation is maximize consumption at the lowest price and at the highest possible satisfaction. Our consumers are sensitive to the vendors' profit margin and will not purchase a product if the profit margin is too large. Whenever a vendor increases its price, consumer satisfaction decreases. As a result, consumers are less likely to purchase from the vendor. At some point in the simulation this will so aversely affect consumer satisfaction that very few of them will purchase the commodity. Once consumers cease purchasing, vendors react to a decrease in their income. Vendors, in turn, have no choice but to lower their price. Once the price has been lowered sufficiently, satisfaction returns to a high enough level for consumers to begin buying again. This consumer behavior keeps the vendors from

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constantly increasing their price and will result in a stablized price. However, as we will see in the next section, there are strict limits on even this behavior which yield control on global price levels.

In our simulation, we model the consumer satisfaction as

$$S = smax[1 - (\frac{1}{e^{t-[\alpha(profit)+(price-\gamma(pricemem))]}})] \quad (18)$$

Here S is the satisfaction, α is a constant that controls the consumer's aversion to profit margin, and γ is a constant that affects competition among vendors. Both of these variables can be initially assigned different values. Profit is the amount of money the vendors make after an exchange is complete. Price is the current price of the commodity and pricemem is the running average of the prices paid by the individual consumer during the last several interactions for the same commodity. The higher the exponent value, higher the satisfaction. Clearly, changing the value of α will alter the consumer's sensitivity toward the profit. Likewise, γ affects the consumer's sensitivity to prices much higher than those recently paid. This indirectly affects competition between vendors.

4 Simulation data

In section 2, we examined the theoretical basis for the design of consumer agents which, we expect, are capable of causing the "invisible hand of the market" to appear, limiting the prices of commodities. Section 3 described our simulation. This simulation consisted of two kinds of agents – consumers and vendors. The two types of agents interact with each other, and have conflicting goals. Moreover, the consumers have a limitation that they *must* have the commodity that is being sold, eventually. Such a commodity might be like water. The consumer agents have the limitation that the longer they go without the commodity in question, the more they're willing to tolerate to get it. As a result, there is potential for price gouging, leading to runaway prices.

In this section, we examine the behavior of the system under the action of the consumer agents. The agents' behaviors are controlled by the equation (18). In this equation, there are two main parameters, α and γ. By changing the values of these parameters, we can produce differing agents behaviors. Some of these behaviors satisfy equation (15) and some don't. We shall see that the desired outcome is achieved when equation (15) is satisfied.

4.1 The effects of γ

In equation (18), we have two parameters, γ and α. γ primarily controls the effect of a high price with respect to previous experienced prices. A high value of γ indicates a high sensitivity to higher prices while a low γ value indicates little or no effect. The overall effect is akin to competition between individual vendors. With a high value of γ, the prices tend to stabilize near those of the agent with the lowest prices, while lower values do not tend to reinforce this.

We can understand this in terms of equation (15). The demand does not change on the left hand side if the prices are all the same. However, the first term on the right hand side is large enough that the equation does not hold. As a result, the price does not reduce, but rather stays constant once all vendors have synchronized their prices. The situation is depicted in Figure 4.1.

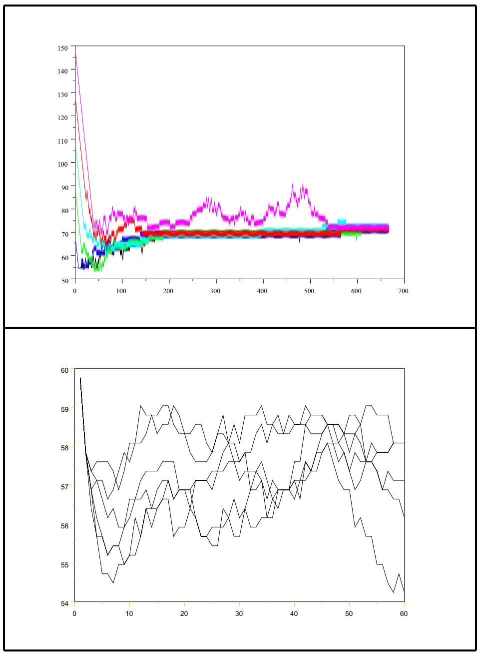

Figure 4.1: With a high value of γ the prices are limited to the lowest price of all consumers. However, if this lowest price is itself high, the prices will not rebound, as can be seen in these figures.

While γ tends to cause competition among vendors, it is not strong enough to cause the control of runaway prices. Consumers are generally stuck with the lowest of the vendor prices. We have seen that the failure of the system to satisfy the theoretical conditions translates to a failure of overall system to produce the desired property. If all of the vendors tend to increase their prices at the same rate (colluding or not), the effect on equation (18) is negligible, and so the condition is still not met. In this case, we can have runaway prices as well. This situation is depicted in Figure 4.2.

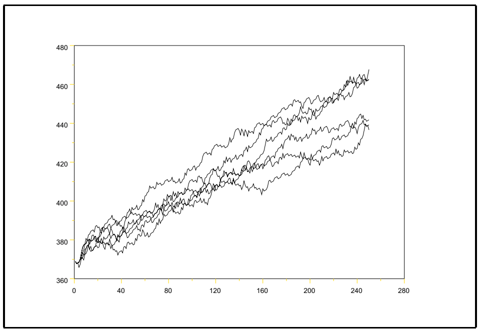

Figure 4.2: Even with a high value of γ the prices can increase unboundedly if vendors continually increase their prices at similar rates.

4.2 Adding in α

It is clear that the competition between vendors is enough to hold most prices equal, but not strong enough to stabilize the cost of the commodities at prices that reflect their actual cost. This is interesting for a great many reasons, not the least of which is that this seems to contradict the "invisible hand of the market" that underlies much of economic theory. Clearly, more than simple competition is required to restore this property.

Satisfying equation (15) requires that another, stronger term become active. In equation (18), the parameter α controls the sensitivity of the consumer to the profit margin that the vendor is receiving. Very high values for α make the consumer intolerant of even small amounts of profit. On the other hand, small values for α make the consumer very tolerant of profits. We examine the effect of this.

The immediate effect is that the decrease in demand as a function of time becomes inextricably tied to the rate of increase of profit. If the profit increases, then the demand decreases. If α is high enough, the decrease exceeds any increase in overall profit associated with increasing the price. As a result, the condition in equation (15) is satisfied, and the price is controlled. The situation is depicted in Figure 4.3.

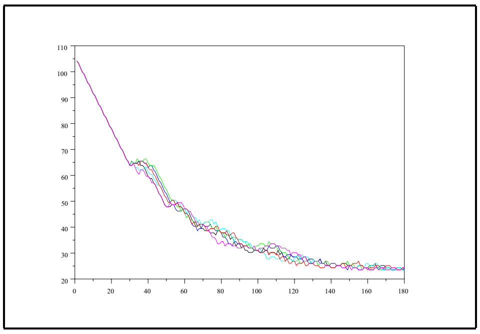

Figure 4.3: With γ high or low, a high value of α is sufficient to control the prices of the commodity. This is expected due to equation (15), and confirmed in this simulation.

Note that in subsection 4.1, we kept α low, and the simulation had a global price increase over time. Only adding this very strong affector seems to hold prices low over time. The effect of this design element is so strong that it can take hold long after the price increase has begun, as illustrated in Figure 4.4.

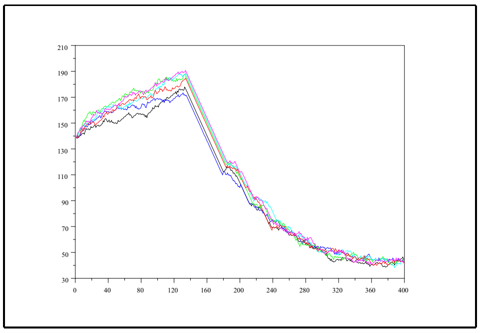

Figure 4.4: If α is initially small, and γ high, the system exhibits slow price increase over time. However, if α is "turned on" at some later time, the system recovers its low-price configuration.

4.3 Examining (15)

One of the main guiding principles of this study has been the need to satisfy equation (15) in generating the consumer behavior. The reason is that we showed in section 2 that if (15) is satisfied, then the behavior will lead to the desired global behavior. We now examine how closely our simulations adhere to this equation in generating the behaviors that limit commodity prices.

We can graph both sides of equation (15) as a function of the simulation iteration number. When we do this for both cases in which the price is controlled and cases in which the price is not controlled, we find that when a vast majority of the data follows equation (15), the prices are controlled. If this is not obeyed, even a bit more than intermittently, the prices are not controlled.

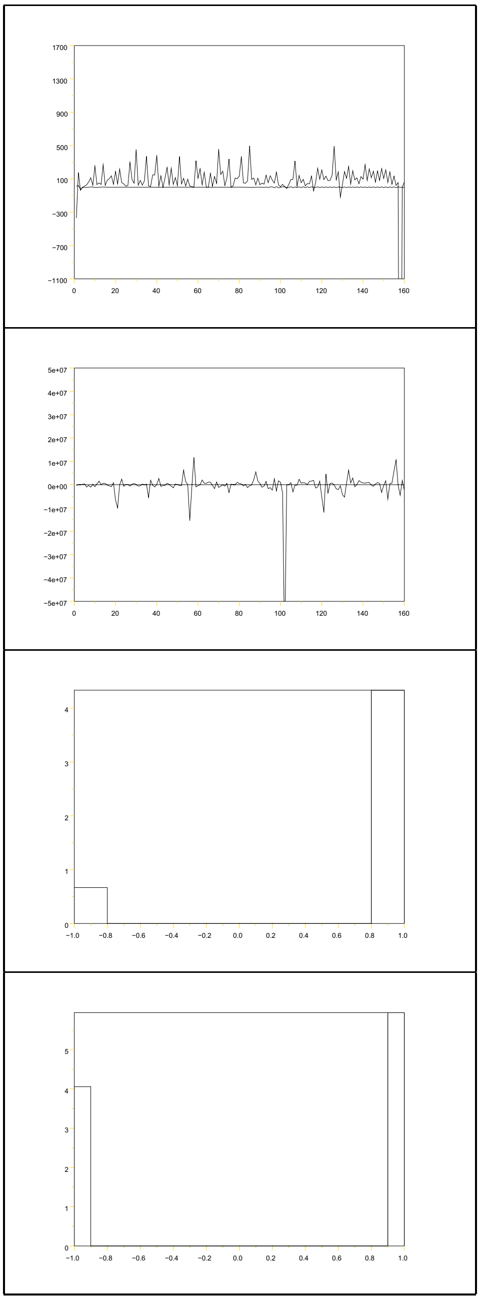

Figure 4.5: These graphs illustrate the values of equation (15) as the simulation is run (top two) and histogram the number of times it is obeyed and not obeyed (bottom two). We find that when the equation is obeyed most of the time (first and third), the prices are controlled. However, when the equation is obeyed considerably less than all the time (second and fourth), the prices are not controlled. This supports our theoretical derivation of this condition.

5 Discussion and conclusion

Designing swarms of agents is a very tricky business, owing to the nonlinear interactions of the various agents. As with all complex systems, swarms of a particular design might have a particular global behavior, but swarms with a very slight difference in behavior may have completely different global behaviors. As a result, predictive design has largely been avoided in the swarm literature.

In this paper, we've explored a method of swarm design in which a specific global swarm behavior is developed prior to the design of the agents. The desired behavior, it has been shown, can be made to order once a set of requirements for agent design is worked out which will mathematically guarantee that the swarm accomplishes the task [6]. Mathematical guarantee, which has eluded swarm researchers previously, is achieved by utilizing the global goal written in terms of the senses and actuators that the agents can be expected to have access to. Once the swarm condition has been met, the global goal may be achieved with agents meeting this condition.

It is interesting to note that this method of designing swarms is similar in form and function to the design of mechanical systems using the Lagrangian method. The power of this method lies in the ability of the engineer to create one or more properties whose numerical values are unique to the state that the system is in. The engineer, then, needs only chart a path through the allowed phase space of the system to the final desired value, hopefully utilizing behaviors which individual agents can accomplish on their own, with or without guidance from a central controller. The method can be applied to single properties or to vectors of properties, provided that the desired vector is well-defined in the same way a single property might be. We believe that the method is so powerful, in fact, that we now coin a term for this method: ***The Hamiltonian Method of Swarm Design***.

This study, which examines the design of an agent based economic system, has demonstrated that in such systems, the achievement of global goals is possible when specific agent traits are required of the agents. It is interesting that such systems can exhibit control that typically comes from "the invisible hand of the market" or from a command economy [17]. In fact, we have unmasked the "invisible hand of the market" in this study, revealing not only where it comes from but under what conditions it functions. It is interesting to ask, in light of the new method of controlling these swarms, what other economic indicators, trends, etc. can be commanded by the agents within the system.

Another interesting aspect of this study is just how fragile the system seems to be in terms of destabilizing under the improper behavior of one or a few agents. As we have seen in section 4, when the inequality (15) is not obeyed, even a little, the prices become uncontrolled. It is interesting, then, to ask whether or not this system is stable in the sense that a few agents do not have the ability to drive the system into this uncontrolled region. This may give us insight into some of the interesting trends seen in recent years in economic systems including overvaluing of various commodities including .com stocks and housing prices. More research on this is clearly indicated.

In the future, we intend to apply this method to swarms of greater complexity than this one. We expect that this method of not only swarm design, but complex system design, may be applied to a large number of different systems including, but not limited to, systems of autonomous mechanical agents, computing systems, economic systems, and social systems. While some of this research is currently under way, we expect that the exploration of all fields to which this methodology might be applied will reveal an extraordinarily vast scope. Moreover, we expect that an extension to this work will be able to solve the problem originally posed ten years ago which led us to these results: "Is it possible that the global specification of a problem is enough to yield the basic requirements of the solution including all actuators, sensors, processing, and other capabilities of agents in the solution?" We believe the answer is yes.

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