Control-Theory Simulation of Buying and Selling Behavior in a Market

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This modeling project offers an alternative to the conventional rational-choice perspective of economists on the behavior of individual investors in markets trading in commodities or securities. Taking a perceptual control theory (PCT) perspective on such behavior, we ask, “What perceptions are investors attempting to control?” We construct simulated actors, who are modeled as having control systems for buying or selling a traded commodity, and report the behavioral patterns of several simulated actors with differing profiles of parameters when confronted with simulated bear or bull markets, where random downward or upward fluctuations in the price of the commodity are taken as disturbances to the perceptions that the actors are modeled as seeking to control. The paper concludes with a description of the differences between a PCT approach and more conventional models of market behavior and an assessment of the advantages and difficulties of taking a PCT approach.

INTRODUCTION

In recent years, crippling consumer, corporate, and public debt, together with historic levels of bankruptcy, default, foreclosure and unemployment have raised questions about economists’ prevailing theories of market behavior. Observers of this contemporary economic confusion have called into question the “classic” models of market behavior, as presented in countless articles and books (e.g., Foxall 1983). While the drastic worldwide economic contraction of 2008-2009 has intensified the importance of understanding the individual motivations of investors in markets, economists’ disjointed responses to market shocks have demonstrated that conventional paradigms for understanding market and consumer behavior have some serious deficiencies (Shiller 2005; Taleb 2010).

Most economic analyses of market behavior have relied on rational choice theories of behavior. Traditionally taken as foundational in economics and widely applied in other social sciences, as well, theories of rational choice begin with the premise that individuals consider the estimated costs and benefits of every choice before acting. This calculation, informed by individual goals or objectives, includes an estimation of external constraints and personal, situational, and systemic influences. Given finite resources, actors carefully weigh available

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options in order to identify the choices that can promise the most beneficial outcomes (Becker 1976; Friedman 1957; Tversky and Kahneman 1986).

In order to model such behaviors, rational-choice theory makes a series of assumptions about the properties of the actor:

1. **Knowledge of alternatives.** Decision makers are modeled as having a set of alternatives for action. These alternatives are defined by the situation and known unambiguously.
2. **Knowledge of consequences.** Decision makers are assumed to know in advance the consequences of alternative actions, at least up to a probability distribution.
3. **Consistent preference ordering.** Decision makers must have objective functions by which alternative consequences of action can be compared in terms of their subjective value.
4. **Decision rule.** Decision makers need to have rules by which to select a single alternative of action on the basis of its consequences for their preferences. (March 1982: 29; Whitford 2002)

Although economists find these assumptions useful for simplifying their mathematical models of markets, these assumptions imply a psychological model of the actor that many social scientists find unrealistic. Indeed, the preeminence of rational choice theories in social sciences is increasingly being challenged (Friedman 1996; MacKenzie, Muniesa, and Siu 2007). The most salient criticisms of rational choice theories focus on the applicability of their central assumptions. In particular, sociologists and political scientists have objected to the scope of presumed knowledge of alternatives and consequences, noting that individuals often do not possess the degree of understanding required by rational choice theories. Similarly, the assumption of consistent preference ordering comes in for criticism because decision makers often do not possess the degree of understanding required by rational choice theories. Perhaps most importantly, the utility of rational choice theories is challenged because people often appear to behave non-rationally or even irrationally (Whitford 2002; Powers 2004; McClelland 2004). Thus, sociologists have criticized theories of rational decision-making as failing to offer a persuasive account of the seemingly irrational behaviors of collective action, altruism, and creation of social norms (Whitford 2002). In many situations, individuals choose actions that do not necessarily maximize personal gain and instead often benefit others far more than themselves. Among behavioral economists, a cottage industry has grown up to rationalize the observed “departures from rationality” that confront any analyst who begins from the assumptions of rational choice theory (e.g., Tversky and Kahneman 1986). In sum, many social scientists have concluded that human behavior cannot be simplified to a series of precise cost-benefit analyses with predictable outcomes, and a critical appraisal of the market gyrations of recent years reinforces the conclusion that the economic behavior of actual investors bears little resemblance to the economists’ model of rational man.

If theories of rational choice appear inadequate to the task of explaining the behavior of investors in markets, what is the alternative? Rational choice theories have held sway in the field of economics for so long that most economists, seeing no obvious theoretical candidate to replace them, continue to subscribe to them in spite of their obvious deficiencies. The purpose of this paper is to suggest an alternative possibility for understanding market behavior—perceptual control theory (PCT)—and to present a preliminary model that illustrates how this theory can be applied to the analysis of decision-making by investors.
In seeking to understand individual behavior, advocates of PCT shift the focus from an actor’s overt actions—for example, the visible results of decision-making—to the actor’s perceptions instead. The theory begins with the assumption that actors seek to control their perceptions, in other words, to keep them relatively stable within the range of their expectations. Putting it more formally, PCT theorists posit that control is a process by which individuals maintain a controlled variable stable relative to an internally held reference condition through actions that oppose the effects of disturbances that might affect their perceptions of that variable (Powers 2004; Powers 2005; Powers 2008; McClelland 2004; McClelland and Fararo 2006).

Because many detailed explanations of perceptual control theory are already available (see the citations above), we will not in this paper repeat the basics of the theory but instead will focus on its possible applications to economics. Although PCT and closely related theories have found many applications in sociology (Burke and Stets 2009; Heise 2007; McClelland and Fararo 2006; Robinson 2007), applications of PCT in other social scientific fields are fewer, and in economics the theory has rarely been applied. So this study represents an exploratory foray into a field in which applications of the theory have yet to be tested.

Our application of PCT to investors’ behavior begins with the question that serves as a starting point for every kind of PCT investigation: What perceptions are the actors in question attempting to control? Perceptions, because they are internal to the actor, are not directly visible to the observer. The control of an actor’s perceptions can have observable effects on the actor’s environment, however, as this process of perceptual control results in a corresponding stabilization of variables in the physical environment that are acted upon by the actor and appear to be the source of the actor’s perceptions.

Our procedure in this investigation will be to hypothesize the variables that investors might be controlling, construct simulation models of “robotic” agents that control those variables in line with varying reference conditions, and examine the patterns of behavior of those agents for a plausible match to the behavior of actual investors. Specifically, we will observe whether the simulated agents buy or sell a traded commodity in the face of market fluctuations and how these transactions then affect their economic position.

Our goals in this investigation are to answer two associated questions: (1) What perceptions are investors attempting to control? (2) What are the advantages and challenges of applying PCT to modeling market behavior? To answer the first question, we have coupled investment research with common sense and have come up with two variables we think likely to be prominent among the perceptions controlled by investors: growth in the value of the agent’s investment in the market, and growth or at least preservation of the agent’s liquid assets. Answers to question 2 will be addressed after we present and evaluate the results of simulations that put our answers to question 1 to the test.

METHODS

We report in this paper on a simulations-modeling study, in which we construct mathematical models of negative-feedback control systems to simulate the relevant behavioral systems of our simulated investors, and then observe their behavior using different combinations of reference conditions for the variables they are modeled as controlling, as well as different patterns of disturbance to those variables. Like Marken (1992) and McClelland (2004, 2006), we use spreadsheets to construct our models of individual behavior.

As with some previous models of control systems (e.g., Powers 2008), our model depicts several closed loops within a larger feedback loop. Specifically, our simulated agents
are modeled as attempting to manage their perceptions by means of two focal control systems that may in some conditions be at odds with each other.

The first control system, which we call *Investment Growth*, controls the agent’s perception of change in the current value of the investment in the market in which trading is taking place. The agent’s reference condition for this perception is a target percentage for growth in the market value of the agent’s investment holdings. If the value of the agent’s investment is perceived to be increasing by approximately the reference percentage, the agent will, in effect, be satisfied and do nothing. If the rate of increase in value is sufficiently greater than the target percentage for growth, the agent will seek to sell some of its holdings of the traded commodity, in effect taking a profit. And if the rate of increase in value of the agent’s holdings is too low or even negative, the agent will attempt to buy additional units of the traded commodity. Whether the rate of increase is too high or too low, the agent’s transactions will tend to bring the growth in value of the agent’s total investment in the market back into line with the reference percentage for growth of its holdings. We have attempted here to model agents who use the time-honored “rational” strategy of selling high and buying low with respect to their own expectations of how fast the market value of the commodity “should” be growing.

Our simulated agent’s second control system is for preservation or even growth of the agent’s liquid assets—cash—and we call this system, *Liquidity Protection*. Again, the reference condition for this control system is a percentage change, which may be zero, positive, or negative. Agents whose supply of cash is growing faster than the reference percentage will seek to invest some of that cash in the market by buying additional units of the traded commodity. Agents whose cash reserves are being depleted relative to the reference percentage for change will attempt to replenish their liquid assets by selling some of the units of the commodity they hold. Again, either action tends to control the agent’s perception of change in its supply of cash by bringing it back in line with the intended rate of change.

Actual investors are no doubt attentive to many other perceptions besides these two in rates of change in making their decisions about investments: for example, the changing market price of the traded commodity, the investment advice of brokers or news media, or even hot tips and other advice from friends and family. However, we did not see an easy way to model our agents as being able to exert control over any of these perceptions. In particular, with regard to the fluctuating market price of the commodity, this variable appears to be entirely beyond the control of the average investor, or indeed of anyone without the enormous resources needed to corner a market. Of course, each individual investor’s actions will have some small effect on the market price of the commodity, tending to raise the price when the investor buys and lower it when he or she sells; however, in a market with many other players the effects of any individual investor’s transactions are all but negligible.

While the changing market price of the commodity did not appear to be a controllable perception, the changing price of the commodity does act as a disturbance to one of the variables our agents are modeled as seeking to control: *Investment Growth*. The value of the simulated investor’s holdings will change with every change in market price. Indirectly, this changing price will also tend to disturb the agent’s perception of *Liquidity Protection*, as the agent adds to or takes away from cash reserves by buying or selling units of the commodity to maintain control of its perception of *Investment Growth*. Thus, we modeled the changing market price for the traded commodity as the most important *Disturbance* in the control loops for our investor’s simulated perceptions.
Readers should note that our agent’s two control systems, *Investment Growth* and *Liquidity Protection*, may in some situations tend to act at cross purposes. If, for instance, the market price of the commodity is rising more rapidly than the agent’s reference percentage for *Investment Growth*, resulting in a correspondingly rapid rate of growth in the value of the investor’s holdings, the simulated investor, to keep its perception of growth in investment value on target, will start to sell some units of its investment holdings. If this sale of holdings then results in a rate of increase for the agent’s liquid assets which is more rapid than the agent’s reference percentage for *Liquidity Protection*, the agent will seek to buy back the units just sold. A similar dynamic occurs when slow growth in the market price of the commodity prompts the buying of a greater stake in the investment to keep its value rising, but this purchase then tends to deplete cash reserves, leading to an “impulse” to sell units of the commodity in order to restore liquidity.

Thus, we have modeled our simulated investors as sometimes experiencing contradictory impulses to buy and sell simultaneously. To control their perceptions, agents must balance the potentially conflicting impulses emerging from the *Investment Growth* and *Liquidity Protection* control systems. Our design of model that is susceptible to internal contradictions builds upon simulations research reported by McClelland (2004, 2006), which showed that conflict between control systems is not necessarily incompatible with effective control. Moreover, the idea of designing a model with the potential for internal conflicts gains additional plausibility when we consider the many control systems built into the human body that sometimes utilize conflict to achieve control, such as pairs of opposing muscles, which may occasionally seize up with unresolved conflicts like charley horses or other muscle stiffness, but also allow for stability and precise control under a wide range of conditions. And we would argue that modeling our simulated investors as vulnerable to being caught in the grip of contradictory impulses may provide us with a believably realistic portrayal of the experiences of many actual investors beset by simultaneous hopes and fears as markets fluctuate.

Figure 1 provides a more detailed depiction of our model for simulating the behavior of an individual investor. Our simulation model is iterative, with more than 500 steps in each run, and each of the variables shown in Figure 1 is recalculated at each step of the iteration. Figure 1 indicates how the variables in the model are related to one another.
Figure 1. Schematic Diagram of the Simulation Model of an Investor

The two horizontal dashed lines across Figure 1 divide it into three panels that indicate a hierarchy of variables and relationships. The bottom panel of Figure 1, the area below the heavy dashed line, comprises variables and relationships external to the simulated investor, phenomena conceptualized as occurring in the investor’s physical and social environment. The rectangles in this part of the diagram stand for variables, and an arrow connecting one rectangle with another indicates that the variable from which the arrow originates contributes
to the iterative calculation of the variable to which the arrow points. The black dots at junction points of the arrows indicate places where arrows join or divide, and a “step up and over” at a junction point indicates a place where one arrow crosses another without joining it.

For example, an arrow connects the Units Bought or Sold variable with Units of Investment. The arrow indicates that the first variable is used in the calculation of the second. In particular, at each step in the iteration Units of Investment is the sum of the units held in the previous step and Units Bought or Sold in the current step (a positive or negative number or zero, depending on whether units are bought, are sold, or no transactions occur). Similarly, we recalculate the Cash Reserves at each step by taking the total of cash reserves from the previous step and adding or subtracting, as the case may be, the product of the current Market Price of Investment times the number of Units Bought or Sold.

The middle panel of Figure 1, above the heavy dashed line but below the lighter dashed line, comprises variables and relationships that we conceptualized as perceptions that are controlled by lower-order control systems within the simulated investor; however, we did not attempt to construct a detailed model of the control-system structure for perception of these variables. We use rectangles with rounded corners to represent the variables in this area, all of which we calculated simply by using a mathematical algorithm for determining their value at each step of the iteration. For example, Current Value of Investment is calculated as the product of Units of Investment and Market Price of Investment. Net Worth is the sum of Current Value of Investment and Cash Reserves.

The top panel of Figure 1, the area above the lighter dashed line, forms the most important part of our model. It shows the two modeled control systems for Investment Growth and Liquidity Protection, with circles labeled as I, C and O to represent their input, comparator, and output functions, and arrows to indicate the internal signals between those functions: perceptual signals link the input and comparator functions, reference signals link higher-order control systems to the comparator function, and error signals link the comparator and output functions.

In the case of the Investment Growth control system, the input function calculates an instantaneous rate of change by taking the Current Value of Investment and dividing it by the value of the same variable at the preceding iteration. The input function then passes that rate of change as a perceptual signal to the comparator, where it is subtracted from the reference signal for the control system, which is targeted rate of change. The resulting difference, the error signal, is passed to the output function, where an output signal is calculated by a formula used for creating models with digital computers to simulate the dynamics of analog control systems (see McClelland 2004). For detailed definitions of the formulas used in this simulation, see Appendix 1.

The Liquidity Protection control system is structured in much the same way as the Investment Growth control system. The input function of the Liquidity Protection control system calculates an instantaneous rate of change, in this case by taking the current value of Cash Reserves and dividing it by the value on the previous iteration. This instantaneous rate of change becomes the perceptual signal which is subtracted by the comparator function from its reference value for rate of change, and the calculations of the error signal and output signal correspond exactly to similar calculations in the Investment Growth control system.

The output signals from the Investment Growth and Liquidity Protection control systems are added together (but with opposite signs, since the two systems are conceptualized as working in opposite directions) and the sum is used as input for a Transaction Control algorithm that determines whether any units of the investment will either be bought or sold at
any given step in the iteration. This determination of how many units to buy or sell is based partly on the sum of the output signals from the two control systems and partly on the simulated investor’s Net Worth: the number of units to buy or sell increases as net worth increases and decreases if net worth falls. The algorithm also contains limitations to prevent the investor from selling more units of the investment than it currently owns or from buying more units than it can afford, given cash on hand and the price of the commodity. In addition, the algorithm places a lower limit on the number of units of the commodity that can be bought or sold in any transaction. At each iteration, output from the Transaction Control algorithm becomes the value for Units Bought or Sold, and in coming back to this variable we have traced our way around the control loops depicted in Figure 1.

Using our control-systems model, we examined hundreds of runs of the simulated buying and selling behavior of individual investors over a hypothetical ten-year period. For each run of the simulation model, we held all starting values and some of the model parameters constant. Each simulated investor began a run with $100,000 in initial cash reserves, as well as 1,000 units of the fictitious commodity worth $100,000 cumulatively ($100.00 per unit), for a total initial portfolio value of $200,000. We based our simulations on an imaginary ten-year period, and we permitted our simulated investors to make no more than one market transaction per week, either by buying or selling a whole number of units of the commodity at the market price for that week. Thus, each iterative step in a run of the simulation model corresponded to a single week of the fictitious ten-year period.

For any one run of the model, we used a fixed vector of 500 or more values of the disturbance variable, which in our model represents the fluctuating market price of the simulated commodity. In our initial exploratory runs of the model, we created vectors of 500 random numbers by adding a random value from a normal (Gaussian) distribution to the values for the previous step in the iteration. After generating a variety of these random-walk vectors, we picked out three patterns to test: one that trended sharply upward to simulate a bull market, one that trended downward to simulate a bear market, a third that went both down and up to represent a fluctuating market. We used these vectors as disturbance variables in our initial runs.

Research has shown, however, that the fluctuations of prices in stock markets do not precisely follow a Gaussian distribution, because sharply upward and downward jumps are somewhat more likely to occur than in a Gaussian distribution (Ball 2004:176). Consequently, to increase the verisimilitude of the runs we will describe in this report, we decided to use a variable based on actual stock-market prices. The disturbance vector we have used for the data reported here is based on the final closing price for the Dow-Jones Industrial Average for 521 consecutive weeks, beginning with the closing average on Friday, June 5, 2000 and ending with the closing average on Friday, May 24, 2010. For ease in discussing our findings, we have rescaled these prices to make the price at week zero of the simulation exactly $100. Our scenario for these simulations, then, is that each investor starts the 521-week sequence with 1000 shares of a fictional stock worth $100 a share on June 1, 2000, as well as $100,000 in cash, and we then simulate the investor’s market transactions until the end of May 2010 on the assumption that the price of the fictional stock rises and falls over those ten years in lockstep with the changes in the Dow-Jones Average. Although this report will describe our results in terms of stock prices, we see our model as also applicable to behavior in other markets, such as commodity markets.

Among the model parameters that we kept constant for all of the simulations reported here were a slowing factor of 0.0001 (a necessary part of the formula that researchers use in
order to simulate an analog process using a digital computer) and a set value of 50 for the minimum number of shares in any transaction, which corresponds to a $5000 purchase or sale at the initial price of the stock. We experimented with different minimums, but found that the behavior of our simulated control systems was a little more stable when we imposed a fairly high lower limit on the minimum allowable size of a transaction. Our thinking, too, was that by putting a minimum size on transactions, which tends to lower the number of transactions, we could increase the realism of the simulations, because a strategy of limiting the number of transactions is rational for investors who want to minimize their transaction costs.

Among the model parameters that we varied from simulation to simulation were the reference values for annual percentage growth in the value of the investment and for annual percentage change in the amount of cash on hand. For purposes of calculation, we divided these annual percentages by 52 to approximate the amount of change to be expected each week in a variable that is increasing or decreasing by the given annual rate. In some of our simulations we also changed the value of the gain parameters for the two control systems in the model. By increasing or decreasing the gain parameters, we could, in effect, see what happens when we turn the individual control systems on or off.

Thus, by systematically varying the parameters of the model from run to run, we were able to investigate a range of investor profiles, and we operated from the premise that while all investors desire to reconcile differences between their perceptions and their reference values, individual investors often vary considerably in their market behavior. For example, day traders generally demonstrate far greater concern for short-term fluctuations in price than investors focused on long-term performance, such as the occasional investor or a mutual-fund manager. Even among the types of long-term investors whose behavior we are attempting to model in this simulation study, we would expect to find a wide range of investment “personalities” in terms of their aggressiveness in pursuing gain or cautiousness in preserving capital. Accordingly, we have selected seven contrasting investor profiles from among the large number of simulations we ran, and in this report we describe our results for these seven profiles. These selected profiles represent some of the extremes in the range of behaviors exhibited by our simulated investors, and we offer them as a reasonable portrayal of the capabilities and limitations of this simulation model.

RESULTS

We begin by presenting results for runs of our simulation model with the seven investor profiles that we have selected to illustrate the range of behaviors that the model exhibits when confronted with a disturbance vector that traces the ups and downs of the Dow-Jones Industrial Average over the decade from 2000 to 2010.

Figure 2 shows this disturbance vector, which we have designated as representing the price of a fictional stock over the ten-year period. The stock’s price, in lockstep with the Dow, takes a steep dip in March 2001, recovers again that summer, but then falls off sharply with the events of September 2001. A modest recovery begins in the autumn of 2001 and continues into 2002, but the price drops abruptly again that summer and reaches a low point in September 2002, down more than 30 percent from its June 2000 starting point. In March 2003 a strong bull market sets in, with the price almost getting back to the June 2000 level in February 2004. A relatively static market, with some ups and downs but very modest overall growth, continues until January of 2006, when a strong bull market begins again, reaching its peak in October 2007 at about 30 percent above the June 2000 starting point. A ferocious bear market ensues: the price drops particularly sharply in the autumn of 2008 and hits a low
of nearly 40 percent below the June 2000 starting point in March 2009. The rest of 2009 and the early months of 2010 see a very strong recovery, but after a short but sharp slide in May 2010, the price ends the ten-year run at about 6% below the price at the beginning of the run. The overall pattern of this disturbance, then, provides a test of our model against a variety of markets, including some vigorous bull markets, a relatively static market, and a couple of bear markets, one of them unusually strong.

Figure 2. Disturbance Vector Used in Runs of the Simulation Model

Table 1 displays the combinations of parameters that we assigned to the seven illustrative profiles in runs of our model. We have designated each simulated investor by a first name in order to facilitate our discussion of their investment “personalities,” and we begin by discussing the results for each investor in turn. Next, we evaluate their comparative successes and failures in the market, and we finish this section with a brief discussion of their behaviors in runs of the model with other disturbance vectors.
Table 1. System Parameters for Simulated Investors

<table>
<thead>
<tr>
<th>Simulated Investor</th>
<th>Investment Growth Control System</th>
<th>Liquidity Protection Control System</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>System Gain</td>
<td>Reference Value</td>
</tr>
<tr>
<td>ALICE</td>
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<td>0.0%</td>
</tr>
<tr>
<td>BARRY</td>
<td>800</td>
<td>20.0%</td>
</tr>
<tr>
<td>CAROL</td>
<td>200</td>
<td>5.0%</td>
</tr>
<tr>
<td>DEREK</td>
<td>1,000</td>
<td>15.0%</td>
</tr>
<tr>
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<td>25.0%</td>
</tr>
<tr>
<td>FRANK</td>
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<td>0.0%</td>
</tr>
<tr>
<td>GRACE</td>
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<td>8.5%</td>
</tr>
</tbody>
</table>

**Alice**

The first profile, Alice, provides an example of a do-nothing investor, and her results will serve as a baseline of comparison for results from the other profiles. In Alice’s case, we have switched off both of the main control systems in our model, the systems for *Investment Growth* and *Liquidity Protection*, by assigning a system gain of zero to both of them. (System gain determines how quickly a control system moves to correct perceptual errors by acting to bring perceptions into line with reference conditions, and systems with a gain of zero do not correct any errors.)

With her control systems not activated, Alice makes no transactions whatsoever, but simply holds on to the same number of shares of the fictional stock and the same total of cash resources from the beginning to the end of the simulated ten-year run. Because the market price of the fictional stock, which tracks the Dow-Jones Average, ends up about 6% lower in May 2010 than it had been in June 2000, Alice’s 100 shares of stock decline in value to $93,903, but she still has her $100,000 in cash (we’re ignoring inflation here), and her final net worth comes out to $193,903, just about 3% lower than the $200,000 that she started with.

**Barry**

Our second simulated investor, Barry, has been assigned a system gain of 800 and reference value of 20% annual growth for the *Investment Growth* control system, but only a system gain of 200 and reference value of 5% for the *Liquidity Protection* control system. Barry might be described as an aggressive investor: his goals and actions are heavily weighted toward seeing his stock portfolio grow briskly, though he also hopes for some modest growth in his cash on hand.

With his strong bias toward getting into the market, Barry embarks on a strategy of buying shares when prices are falling or static and then holding them through any sharp upswings. By the peak in the market in October 2007, Barry’s stock portfolio has grown to more than 1800 shares, worth nearly $240,000, although his cash supply has dwindled to about $30,000. In comparison to Alice’s total holdings at this point, Barry’s net worth of
$269,000 puts him nearly $40,000 to the good. But the big crash in 2007-2008 hits Barry hard, partly because he keeps buying aggressively throughout the downswing, and by the time the market bottoms out in March 2009, he is virtually out of cash and thus can buy no more shares. His stock holdings have grown to 2130 shares, but they are worth only about $131,000 at this point. Barry’s total holdings are down by more than 50% from the 2007 peak.

Barry’s stock holdings rebound nicely in the bull market of 2009, and by April 2010 his 2130 shares are worth more than $217,000, but with the modest downturn in May 2010, he ends the run with just $200,023 in net worth, a mere $23 more than he started with in June 2000. Barry can still congratulate himself that by breaking even he has done better overall than Alice, who lost 3.0%.

**CAROL**

Our third investor, Carol, has been assigned a system gain of only 200 and a reference value of 5% annual growth for the Investment Growth control system, but a system gain of 800 and reference value of 20% annual growth for the Liquidity Protection control system. With this strong tilt toward disregarding her stock portfolio in favor of seeing her cash reserves grow, Carol’s personality as an investor contrasts sharply with Barry’s; she is just as conservative as he is aggressive.

Carol begins the ten-year run by just sitting on her hands for the first year or so, as the market bounces around without any strong trend, but when the price of the stock starts trending sharply downward in September 2001, Carol begins systematically to divest herself of around 50 shares of stock every several months. She sells a bit more rapidly on upswings in the market than on downswings, but she maintains this strategy throughout the bull market of 2006-2007 and even sells one more parcel of shares midway through the crash of 2008. By the time the market hits bottom in early 2009, Carol is holding only 20 shares of stock, and her cash reserves have increased from the starting value of $100,000 to about $193,000.

As the market begins to rise again in 2009, Carol sells her last shares of stock but almost immediately buys back another 203 shares, which she holds as the market recovers until the end of the run. Although by April of 2010 she has made about a $5000 profit on her $16,000 investment in the 203 shares she bought in November, the market slides back in May, and she ends the run with a net worth of $197,972. This loss of 1.0% from her starting values is not quite as bad as Alice’s 3.0% loss, and although Barry’s net worth exceeded Carol’s by almost $70,000 at the market peak in October 2007, and Carol’s exceeded Barry’s by about $63,000 at the market bottom in March 2009, they end the run just about $2000 apart.

**DEREK**

Our fourth investor, Derek, has been given an identical set of parameters for the two control systems in our model: each control system is assigned a gain of 1000 and reference value of 15% annual growth. One might consequently describe Derek as a very balanced investor, paying equally close attention to the growth of his stock portfolio and the growth of his cash reserves. Alternatively, one might see him as a highly conflicted investor, unable to prioritize one or the other. In any case, he appears to follow a cautiously measured strategy of investment, with transactions that are fairly widely spaced and include both purchases and sales. His pattern of transactions, shown in Figure 3, is worth looking at in some detail.
Figure 3. Market Price of the Stock in Dollars (x10) and Derek’s Transactions

Like the previous investors, Derek simply sits on his hands during the first year of the simulation, but immediately after the market dips sharply in September 2001 Derek reacts by buying 65 shares of stock. Figure 3 shows this stock transaction by a step upward of the line for shares held, as well as a step downward of the line for cash on hand. Derek waits about a year to make his next transaction, the purchase of another 54 shares of stock, which occurs immediately after the market hits a low in October 2002. Yet another a year passes before his next transaction, which is the sale of 54 shares of stock in December 2003, just as the price is rising rapidly near the end of the 2003 bull market. Derek then does nothing for more than two years, during the relatively static market of 2004-2005.

As the market starts to rise again in January 2006, he sells some stock, and he makes another sale in November 2006, and yet another in July 2007 with the vigorous bull market nearing its peak. During the rest of 2007 and early 2008, as the bull market falters and a bear market takes over, Derek does nothing at all, until the very rapid price decline in October 2008, when he buys 51 shares of stock and the next week buys another 74. He makes another double purchase of 58 and 65 shares of bargain-priced stock just as the market is reaching bottom in February and March of 2009. Once the market recovery has been well established
Derek starts selling stock again, with transactions in August 2009 and again in November, and one last transaction in April 2010, just before the price starts down again in May.

After transactions that have amounted in total to only a couple hundred shares of stock, Derek ends up with 997 shares in his portfolio, 3 less than he started with, worth only $93,622 when the simulation run ends. But his shrewdly timed transactions have netted him a profit of $10,953 in cash, and his final net worth comes out to $204,973. This 2.3% gain compares to Alice’s 3.0% loss, and it also compares favorably to Barry, who just broke even, and Carol, who lost 1.0%. Derek’s tightly controlled style of investing has earned him modestly positive results, even in a market that trended slightly downward.

ELENA

Compared to Derek, our fifth investor, Elena, is something of a free spirit. Elena was assigned a system gain of 1000 and reference value of 25% for her Investment Gain control system, while her Liquidity Protection control system is assigned a gain of zero or, in other words, completely turned off. Giving no attention to whether she is running out of cash, Elena just wants to see her stock portfolio growing briskly. Like Barry, she is a very aggressive investor, but without any concerns about liquidity to hold her back.

Not surprisingly, Elena displays a strong preference to get her money into the stock market, rather than sitting on cash. As soon as the market takes its first minor downswing in March 2001, Elena starts buying stock, with her purchases totaling to about 170 shares in March and another 200 when the market dips again in September 2001. She continues to make a rapid string of purchases as the market drops in 2002, and by the time the market has hit bottom and begun to recover in March 2003, Elena has more than doubled the number of shares in her portfolio, to a total of 2190, but she is left with less than $4500 in cash. Elena seems happy at this point to sit back and watch the value of her stocks grow rapidly during the bull market of 2003, but when the market flattens out again she seeks to resume making purchases. Unfortunately, her purchase of 48 shares in May 2004 has left her with just $11.68, and, lacking the ready cash, she has no choice but to ride out the market the rest of the way. It seems that she would have happily gone into debt to buy more shares, had we let her.

With the market fluctuations in the second half of the decade, it’s kind of a wild ride for Elena: her 2238 shares of stock appreciate to more than $292,000 in value by October 2007, but then their value drops by more than 50% to a little over $137,000 in March 2009. Finally, her stock holdings rebound nicely in bull market of 2009, and, with $11.68 still left in her pocket, Elena finishes her run with a net worth of $210,167. Elena ends up about $16,000 better off than Alice, and her 5.1% gain overall is the best record so far among our simulated investors.

FRANK

Our sixth investor, Frank, appears to be as risk averse as Elena is risk tolerant. Frank’s Investment Growth control system is completely turned off, and his Liquidity Protection control system has been assigned a system gain of 1000 and reference value of 25%. His investment strategy, predictably, is to systematically pull his money out of the stock market. Like Carol, Frank might be called a conservative investor, but he takes it to an extreme.

As soon as the market takes its first dip in March 2001, Frank starts selling stock, and then he sells off his shares in transactions of 50 to 55 shares every month or two, right through the 2001-2003 downturn, selling shares most quickly when the market goes down
most sharply. In September 2003, he sells his last 7 shares and is then left with $183,579 in cash. Since he makes no further transactions, his net worth is still $183,579 when the simulation run ends in 2010. Frank’s 8.1% loss in wealth leaves him more than $10,000 poorer than Alice, and even less well off compared to all of the other investors we have examined, but, looking on the bright side, we can imagine that his strategy has freed him from any worries about the market fluctuations of 2007-2010.

**Grace**

Our last simulated investor, Grace, has been assigned a system gain of 1000 and a reference value of 8.5% for the *Investment Growth* control system. Like Elena, Grace is assigned a system gain of zero for *Liquidity Protection*, turning off that control system. Grace’s combination of a high gain but a rather low reference value for *Investment Growth* was chosen because it was the optimal set of parameters from among the investor profiles that we explored for maximizing overall returns, when tested against the disturbance vector derived from ten years of data from the Dow-Jones Average. While Grace pays no attention at all to her cash on hand, her rather restrained investment strategy involves timing her transactions carefully, buying stock only when the price drops sharply, and then holding her stock through the upswings, selling only when an upswing is extremely strong. This strategy proves successful in our simulated ten-year market.

Figure 4 shows Grace’s transactions, and it shows that Grace makes her first big purchases of stock when the prices take a sharp dip in September 2001. In July and September of 2002, with the price dropping further, Grace buys stock again, making yet another purchase just as the market has begun to rebound in March 2003. Her stock portfolio has grown at this point to about 1450 shares, 45% more shares than she started with, and because she has been buying as the price goes down, her cash supply is down by only about a third, to approximately $66,000. She then waits out the long rise in the market from 2003 to 2007. At the market peak in October 2007, her stock, which was worth about $106,000 in March 2003, has risen in value to $189,000, and with her $66,000 in cash reserves, her net worth has reached $255,000.
Figure 4. Market Price of the Stock in Dollars (x10) and Grace’s Transactions

Grace continues sitting on her hands as the market begins to tumble in late 2007 and the first half of 2008, but when the bottom really begins to drop out of the market in September and October 2008, Grace systematically starts making large purchases, and by the time the market has finally hit bottom in March 2009, Grace has converted nearly all her available cash into more than 2300 shares of stock. By the end of her buying spree, Grace has acquired stock worth just over $155,000, but she is down to less than $20 in cash. Luckily for Grace, the market begins a vigorous recovery in 2009, and Grace is able to do a little profit-taking, selling about 450 shares of the stock purchased at less than $70 a share in March for almost $100 a share in December 2009 and another batch at more than $100 a share in April 2010. These sales bring her cash on hand back up to $10,611, and with her shares of stock worth $207,714 in May 2010, her net worth ends the run at $218,325. Grace’s 9.2% growth in wealth over ten years is relatively modest—less than 1% a year—but she has secured it in a market that trended downward by 6%, and her gains have easily outpaced the 5.1% of her nearest competitor, Elena.
Figure 5. Simulated Investors’ Net Worth on Given Dates

Figure 5 compares the holdings of the seven simulated investors over time. This graph shows changes in net worth on dates that we have picked out as marking significant shifts between bull, bear, and stagnant markets for our fictional stock. One can see from the graph that although the investors are all pretty closely bunched at the end of the ten-year run, their trajectories over the ups and downs of the market show a fair amount of variation. The three most aggressive investors, Elena, Barry, and Grace, take advantage of the bull markets in 2003-04, 2006-07, and 2009-10, but then suffer big losses in the fierce bear market of 2008. The trajectory of the balanced investor, Derek, closely traces that of the do-nothing investor, Alice, although by the shrewd timing of his small transactions he gains a slight but increasing advantage over Alice. The least aggressive investors, Carol and Frank, see little change in their totals, but their great disadvantage in bull markets becomes an advantage in bear markets. Obviously, no single strategy of investment can give an optimal result in every type of market, and if we had ended our simulation at a different point we would have had to pick
out a different profile as the “winning” investor. In this set of runs, Grace’s advantage over the others doesn’t emerge until the very end.

We conclude that our investors’ success or lack of it depends strongly on the ups and downs of the particular markets they face. Some additional runs of our model using other disturbance vectors strengthen this conclusion. We tested our seven simulated investors against the three disturbance vectors that we had used in our first exploratory runs of the simulation model. As we explained above, these vectors were derived from Gaussian random-walk data rather than data for ten years of the Dow-Jones Average.

Figure 6 displays these random-walk vectors in comparison to our Dow-Jones disturbance vector. The first of these vectors, the one we call Bull Market, rises very sharply for the first 200 iteration steps in simulation runs with this disturbance, then fluctuates for about 150 steps and then trends upward again for the last 150 steps to reach a closing price for the fictional stock that is more than three times the price at the beginning of the run. The second vector, which we labeled Bear Market, trends downward for the first 300 iterations and then bounces around until the end of the run at prices that are about a quarter to a half of the opening price for the run. A third vector, which we have labeled Down-Up, trends downward like Bear Market for the first 300 steps, but then takes a modestly upward trend for the last 200 steps of the run. By comparison, the vector we used for the runs reported above, labeled Dow-Jones in Figure 6, fluctuates over a narrower range than these other vectors.
Figure 6. Comparison of Four Disturbance Vectors

Table 2 shows comparative results for our seven simulated investors when we use them in runs with these three other disturbance vectors. We report their net worth at the end of the run, as well as a rank order from the most to least successful for each disturbance vector. Not surprisingly, our most aggressive investors, Elena and Barry, are the most successful investors in the Bull Market, but it may come as a surprise that Alice, who simply holds on to her initial shares, is next in line. Grace, who seemed so clever in the Dow-Jones simulation, is left trailing far behind, with uptight Derek slightly edging her out. Even the most conservative investors, Carol and Frank, make a tidy profit in the Bull Market, though not nearly as much profit as the others.
Table 2. Simulated Investors’ Final Net Worth with Three Different Disturbance Vectors

<table>
<thead>
<tr>
<th>Name</th>
<th>Bull Market</th>
<th>Rank Bull</th>
<th>Bear Market</th>
<th>Rank Bear</th>
<th>Down-Up Market</th>
<th>Rank Down-Up</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALICE</td>
<td>$409,396</td>
<td>3</td>
<td>$131,364</td>
<td>5</td>
<td>$160,491</td>
<td>3</td>
</tr>
<tr>
<td>BARRY</td>
<td>$418,147</td>
<td>2</td>
<td>$85,098</td>
<td>6</td>
<td>$162,843</td>
<td>2</td>
</tr>
<tr>
<td>CAROL</td>
<td>$332,544</td>
<td>6</td>
<td>$162,367</td>
<td>3</td>
<td>$149,105</td>
<td>4</td>
</tr>
<tr>
<td>DEREK</td>
<td>$370,311</td>
<td>4</td>
<td>$162,640</td>
<td>2</td>
<td>$141,427</td>
<td>5</td>
</tr>
<tr>
<td>ELENA</td>
<td>$439,549</td>
<td>1</td>
<td>$68,375</td>
<td>7</td>
<td>$110,489</td>
<td>6</td>
</tr>
<tr>
<td>FRANK</td>
<td>$309,172</td>
<td>7</td>
<td>$188,678</td>
<td>1</td>
<td>$194,063</td>
<td>1</td>
</tr>
<tr>
<td>GRACE</td>
<td>$366,420</td>
<td>5</td>
<td>$141,262</td>
<td>4</td>
<td>$80,757</td>
<td>7</td>
</tr>
</tbody>
</table>

In the Bear Market, everyone loses money, but Frank, who rapidly liquidates all of his shares, loses less than the others. Interestingly, Derek is able to make some profitable trades as the market bounces around at the end of the run, and so ends up in second place, edging out conservative Carol, who has gotten rid of most of her stock. Grace does slightly better than Alice in this run, and considerably better than Barry and Elena, who are heavily invested in shares that have become practically worthless (but would be great to have if the market ever turns up again).

In the Down-Up Market, Frank again is the winner, but Barry has done relatively well, better than both Alice and Carol. Barry buys stock less rapidly than super-aggressive Elena and manages to time his purchases so that the majority of them occur as the market is reaching its bottom. With all these bargain-priced shares, Barry is positioned nicely to enjoy the ensuing recovery in prices, and at one point his net worth even tops his initial $200,000 before it drops back at the end of the run. Grace, who did so well against the Dow, is left completely flat-footed in the Down-Up market pattern, buying stock frantically near the bottom of the market, but then selling it off just as rapidly before the market really starts going up again. She ends this run in last position. Clearly, no investor who is like our simulated investors—stuck with one unvaried strategy for buying and selling, or in other words, one set of reference conditions for controlling the crucial perceptions—can do well in every kind of market.

DISCUSSION

In this study we have proposed a perceptual control-system simulation model for the behavior of individual investors making transactions in markets like commodity or stock markets, and we have shown how the model performs by presenting results for a range of profiles representing simulated investors facing disturbance vectors that represent changes in the price of the traded commodity or security. We offer this research as an exploratory study with many obvious limitations. The most important limitation is that the model that we have proposed is rudimentary, focusing on the control of only two of the many different perceptions that investors may attend to in making their investment decisions, although we
would argue that these perceptions are probably important ones for most investors, focused as they are on the investor’s own bottom line. We may, however, have wrongly specified these perceptions or missed other perceptions that are crucial to the behavior of real investors. Perhaps, for example, a better model would specify the perceptions to be controlled as longer-term changes in the crucial variables—say, monthly or quarterly changes—rather than the week-to-week changes that are the focus of our current model.

Another important limitation of this study is the decision to focus our model on the behavior of single investors rather than on the dynamics of many interacting agents. A multi-agent simulation model similar to those used by economists studying markets (Lux and Marchesi 1999) may eventually be possible to implement using PCT models, but we saw this as too challenging for the kind of exploratory research reported here. One important difference between PCT models and those previously proposed by economists is that the PCT models with individual profiles of parameters will make it possible in principle to take account of individual differences among actors, whereas the models put forward by economists have made use of simulated actors that are all identical and interchangeable. However, the task of creating models with large numbers of simulated actors that have individual differences is likely to present some serious technical challenges for future PCT investigators.

Yet another limitation of our study has to do with its realism. For the sake of simplicity, we have limited our investors to making their transactions in only one fictitious stock, rather than a portfolio of investments. We have also ignored such real-life contingencies as the effects of inflation, changing interest rates, and possibility of going into debt to make purchases.

More seriously, although our model purports to describe the behavior of individuals, we have not attempted to compare the results of our simulations with the actual behavior of any individual. Instead, we have been content with producing simulated behavior that offers a semblance of plausibility. Thus, we cannot claim to have actually tested our model against any empirical data. Getting data on the actual investment behavior of individuals may pose some challenges for future PCT investigators, although the obstacles to gathering these data may not be insuperable, particularly if the task is undertaken in a laboratory setting.

Finally, in discussing limitations of this study, we wish to emphasize that our objectives have been entirely theoretical and that we do not see this research as having had any practical significance. Although future research along these lines may eventually offer insights that make contributions at a practical level, we want to caution readers not to put too much stock in conclusions to be drawn from the behavior of the crudely preliminary simulation models reported here. Thus, any readers who wish to draw investment advice from our study must do so entirely at their own risk. We make no guarantee, real or implied, that using our formulas is a good way to make money!

Whatever the limitations of the study, we do see it as having made some significant contributions. First of all, we think that this study has demonstrated that PCT can offer an interesting and potentially fruitful alternative to the more established approaches to understanding economic behavior. The kinds of advice often given by investment professionals seem to be clearly reflected in experiences of our simulated investors, such as the truism that bull markets reward bold investors and that an adaptable approach (aggressive investing during runs, conservative investing during falls) is the most effective method for maximizing returns and diminishing losses (Buffett 2008; Carlson 2007). Our simulations
reinforce the conclusion that an inflexible approach to investing does not work well in every kind of market.

As we examined our results, we considered the possibility that adding another perceptual level to our simulation model might allow our simulated investors to adapt their market strategies to changes in the market. Figure 7 offers a proposed model for a simulated investor with some built-in flexibility, which is achieved by including in the model a higher-order control system that can vary the reference values for the rates of change to be targeted by the investor’s control systems.
Figure 7. Proposed Model for Simulated Investor that Adapts to Market Conditions.
Figure 7 is identical to Figure 1—the model we have used in this study—except for the inclusion of a top panel that depicts a hypothesized higher-order control system, which we have not attempted to model in this study but that we regard as a good candidate for inclusion in some future investigation of investment behavior. This control system for *Aggressiveness in Investing* would take as its input a weighted combination of the perceptual signals for the *Investment Growth* and *Liquidity Protection* control systems—the instantaneous rates of change in the value of the investment and the cash on hand—and would return as its output two rates of change that would serve as reference signals for the two control systems central to our model. Ideally, the weightings of these connections would be determined by a built-in reorganization algorithm (see Powers 2008).

In our current model, we have explored various combinations of reference signals for the two control systems simply by imposing the reference signals as constant values throughout a given run. Simulated investors constructed along the lines of the model in Figure 7 would be able to change their reference signals and thus shift investment strategies in response to changes in market conditions. An even better version of this simulation model would be able to learn by reorganization the most successful ways of perceiving changes in the market and making the necessary adjustments.

We see our study as having made a couple of additional contributions to PCT modeling by breaking some new ground. One innovation has been to include two potentially conflicting control systems operating at the same level of control in the design of our model; such models have not been used except for modeling pairs of opposing muscles in Powers’ model of the movements of a simulated human hand and arm (2008). Another unusual feature of our model is that control of the focal perceptions is achieved by means of output actions that are intermittent rather than continuous. Many higher-order perceptions in humans must be controlled in this way, because people give attention to such higher-order perceptions only intermittently, but ours is the first study of which we are aware that attempts to model such discontinuities.

We see a final contribution of this study in the fact that we found it easy to enliven the Results section by giving names to our seven simulated investors and bestowing imagined personalities upon them. Although a skeptical reader could easily dismiss this bit of anthropomorphizing as no more than a rhetorical gimmick for brightening up our report of numerical findings, we nevertheless see this ploy, to the extent that it was successful, as demonstrating an important conclusion to be drawn from this study. Several of our simulated investors behaved in ways that to an outside observer would appear to be rational. They sold high and bought low, sometimes timing their transactions exquisitely to take advantage of changes in the market. However, these simple robots possess none of apparatus of rational thinking that such rational behavior would seem to require.

None of the assumptions of rational choice theory apply to our robotic investors. They do not possess any unambiguous knowledge of alternatives, any sophisticated foreknowledge of the consequences of their actions, any objective and consistent preferences for ordering these consequences, nor any decision rules for selecting the single best alternative for action (March 1982:29; Whitford 2002). These simulated investors simply aren’t capable thinking in the contemplative and deliberative manner that such rational decisions are assumed to require. In fact, it’s doubtful that they could be said to be *thinking*, at all. All they are doing is trying to keep in control their perceptions of two variables (and for some of our simulated investors, just one variable). Yet, they can produce behavior that is ostensibly rational, at least from some points of view.
We have, then, two contrasting conceptual models for understanding economic behavior. The long-established model, rational choice theory, is backed by decades of economic tradition and research, and its assumptions facilitate the construction of the kinds of complex mathematical models that represent the latest in cutting-edge economic theory (MacKenzie et al. 2007). However, the assumptions that this theory makes about human behavior are implausible at best, and the rational choice model has failed to give contemporary observers much insight into how and why current economic crises have unfolded.

The alternative conceptual model, perceptual control theory, is still a fledgling in terms of research, but it rests on assumptions that are arguably far more plausible when applied to everyday human behavior, and it differs from the rational choice model in taking seriously the facts of human diversity and individual differences. However, despite the fact that perceptual control theory builds upon a mathematical model that is relatively simple to implement, future researchers who seek to apply that model in any detail to complex economic interactions will face some challenging tasks.

Both theories can claim some clear applications to human economic behavior. The kind of contemplative thinking that rational choice theorists envision, with the actor engaged in a clear-headed and deliberative weighing of alternatives and careful selection of the most rational course of action, must surely be part of the human behavioral repertoire, at least for some people some of the time. More often, however, people are likely to be making their economic decisions, like most other decisions, on impulse and in the thick of the action, without taking the time for any extended rational contemplation (see Bourdieu 1990:11).

Thus, the PCT model of the actor engaged in controlling a small number of immediate perceptions may describe most economic decisions pretty well. And this study has shown that actions that appear rational to the outside observer can be the product of rationality that is built into the perceptual and behavioral organization of the actor, without the need for resorting to complex thinking processes. Perceptual control theorists claim, moreover, that PCT principles can be extended to model the more rationally deliberative thinking processes (Powers 2005), although they have not yet offered any fully worked-out models with that degree of complexity.

We conclude, then, that although both theories have their pluses and minuses, the rational choice theory appears to be incomplete, possibly useful for making ivory-tower descriptions of economic processes on the grand scale, but increasingly implausible as we get down to the level of real people making real economic decisions. By contrast, the perceptual control model, although relatively untested as yet, offers an intriguing alternative for understanding economic behavior from the ground up.

REFERENCES


**APPENDIX 1. FORMULAS USED IN OUR MODEL**

List of Variables and Abbreviations:

- \( D \) = Disturbance (Market Price of Investment)
- \( R_{IG} \) = Reference signal for Investment Growth control system
- \( P_{IG} \) = Perceptual signal for Investment Growth
- \( O_{IG} \) = Output signal for Investment Growth
- \( R_{LP} \) = Reference signal for Liquidity Protection control system
- \( P_{LP} \) = Perceptual signal for Liquidity Protection
- \( O_{LP} \) = Output signal for Liquidity Protection
- \( S \) = Slowing factor
- \( G_{IG} \) = System gain for Investment Growth
- \( G_{LP} \) = System gain for Liquidity Protection
- \( T \) = Transaction Control output quantity
- \( U_T \) = Units (shares) bought or sold
- \( M \) = Minimum size of a transaction in number of units
- \( U \) = Current number of Units of Investment owned
- \( V \) = Current Value of Investment
- \( C \) = Cash Reserves
- \( W \) = Net Worth
List of Iterative Formulas (for iteration $i$):

IF $V_{i-1} > 0$: $P_{IGi} = V_i / V_{i-1}$

IF $V_{i-1} = 0$: $P_{IGi} = 0$

$O_{IGi} = O_{IGi-1} + S \{ G_{IG} (R_{IGi} - P_{IGi}) - O_{IGi-1} \}$

IF $C_{i-1} > 0$: $P_{LPi} = C_i / C_{i-1}$

IF $C_{i-1} = 0$: $P_{LPi} = 0$

$O_{LPi} = O_{LPi-1} + S \{ G_{LP} (R_{LPi} - P_{LPi}) - O_{LPi-1} \}$

$T_i = 1.25 \{ W_i (O_{IGi} - O_{LPi}) \}$

IF $| \text{Round} (T_i / D_i) | > M$: $U_{Ti} = \text{Round} (T_i / D_i)$

IF $| \text{Round} (T_i / D_i) | < M$: $U_{Ti} = 0$

$U_i = U_{i-1} + U_{Ti}$

$V_i = U_i (D_i)$

$C_i = C_{i-1} + U_{Ti} (D_i)$

$W_i = V_i + C_i$