Adaptive functions in an agent-based model of an economic system

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# Abstract

Agent-based models, with a history reaching back to the 1940s, have been cited as a useful technique for planning economic development and simulating the effect of economic crashes. These models offer an insightful alternative to the traditional techniques of mathematical modelling. Understanding how different designs of agent-based models change simulation outcomes will be useful for modellers of economic and other simulation scenarios. The work presented here examines how a computer simulation of an agent-based model responds to disruptive events, in the context of an economic model. Agents within the model interact by producing, selling, and buying goods. A series of experiments compare system stability in two scenarios: one where a top-down rule is applied to the pricing of goods, and another where decision making is at the individual agent level, a bottom-up approach. These two approaches are termed system-adaptive and self-adaptive. Results draw the conclusion that a self-adaptive function can provide greater stability, but this depends on whether the measured variable is a primary or secondary variable to the adaptive function. Considerations are presented for future work which could consider the impact adaptive functions have on secondary variable measurements.

Keywords: Agent-based model, Stability, Simulation

# Introduction

Just as economists and ecologists strive to comprehend the complex systems in which we live, it is also necessary to understand why computer simulations, which reflect real-life systems, behave in the way they do (Bouchaud, 2008). This report will detail experiments and observations relating to the response and recovery (the resilience) of a system to disruptive events. Specifically, the system will be tested under two states: one with greater autonomy for agents to change their local environment by making use of a *self-adaptive function*, and an alternative state with a system-wide rule, a *system-adaptive function*. Experiments will compare the two states, and also how they respond and recover to a disruptive event – suggesting that one state might be more resilient or stable than the other.

The context for the simulations will be an economy where agents produce, sell, buy and consume goods, but the findings could be useful to other scenarios. There is a great deal of interest in the stability of systems, both real and virtual (Biggerstaff et al., 2020; Bouchaud, 2008; Chen et al., 2019), and experiments will measure and compare this in each state case.

## Understanding Simulations

Although this research applies a context to an economic simulation the aim of the work is more general: how do top-down and bottom-up simulations compare when measured? The work will provide modellers with an example of how simulation data can be analysed during and after disruptive events, and how to design models with behaviour for providing system resilience. Models and simulations are inevitably a simplification (Miller, 1969) and so the choice of the inputs and behaviour is critical to producing both realistic and useful results.

Minsky (1992) hypothesises that the critical actors in an economic system become less sensitive to the possibility of failure when an economy is growing. Continued economic growth encourages risks which are more likely to be profitable, which in turn results in instability, and the economic system becomes less resilient to shocks. From the perspective of a practitioner of agent-based models, understanding the measures which make a model resilient, and how it recovers is useful because: crashes are inevitable (in ecosystems too - see Holling & Meffe (1996)); and crashes are unpredictable (Satinover & Sornette, 2010).

Bouchaud (2008) in the wake of the 2008 financial crisis, put it that there is too much confidence in the models of classical economics, and calls for innovative solutions which are bound in the reality that markets are inefficient. Humans can become too focused on short term rather than long term outcomes and the amplification of errors can lead to panic and crashes - “Free Markets are *wild* markets”. Innovative financial products, it is proposed, should therefore be crash-tested in the same manner as innovative products in the pharmaceutical, aerospace and nuclear energy industries.

Hoover (2016) examines the crisis in the role of economic theory in the perspective of the 2008 financial crisis, also drawing on the work of Orléan & DeBevoise (2014) - that a system is radically uncertain and no infallible prediction exists. Hoover concludes that economists may only choose an outcome which suits them best. Instead, rather than trying to change economic systems, understanding the behaviour of such systems should be their primary concern.

Egli et al. (2019) argue that understanding the resilience of agent-based models – how the models absorb pressures, and sustain function is a major challenge. The mechanisms of resilience in general are poorly understood, and this makes it difficult to find a specific situation in which these can be assessed. Resilience and stability (see section “Why Resilience and Stability” for a definition) is a fundamental theme of this work.

Perc (2017) states that while a model in context is useful for understanding the context specifically, it is also useful for understanding models in general. Understanding the stability of the subsystems of a system will provide a satisfactory answer as to why phase transitions occur in a system, which again is a theme of this report.

Craglia (2018) discusses how AI is a necessary tool for policy decisions and is likely in future to be commonplace, supporting the arguments of An (2012) when they state the case for improved modelling of human decisions.

To ask *why* we model in addition to *how*, is necessary to justify the work put into improving models and their simulations. McBurney(2012) summarises this when asking ‘What are models for?’, and in review of other authors work (e.g. Rubinstein, 1997) sets out a list of 12 reasons for modelling. Perhaps the most relevant reason given, in relation to this work is *To understand, predict or control a future human model or artefact.*  If, when modelling decisions taken by either state or (alternatively) individuals, which is the focus of this work, how can we design models such that they reflect the real-world scenario they are modelling, and, how might we implement features which ‘improve’ or change the model. Understanding what makes models more, or less, stable, and resilient, is helpful to install the confidence in the modeller, and perhaps also the decision maker, that the model reflects its real-world equivalent. There are conflicting reasons for modelling, as detailed by McBurney and the other authors referenced in his work, but this work steps back from those to simply ask *why do models behave in the way they do*?

Marks (2007) outlines that models exist to *explain, predict* and *explore* and that to draw confident conclusions the method of validation should be trusted by those other than the modeller. Marks outlines the difficulty in validating models and provides a general framework for doing so. The work outlined here may help the validation process by improving the modellers understanding of why their simulation behaves in the way it does.

## Why improve Agent Based Modelling?

Agent-based models (ABMs) are a methodology for modelling complex systems such as economies. Mathematic models have for many years dominated the simulation space for predicting system outcomes, from population growth to Newtonian physics. Wolfram (2002) challenged the limitations of mathematical models when defining the term *computational irreducibility* – that uncertainty in complex systems, due to the number of interactions and diversity of behaviour, means that it is impossible to predict the outcomes of simulations. Therefore, while a mathematical equation may give a predictable conclusion to an event, complex systems such as ecologies and economies are better served by simulations which allow observation, experimentation, and help to increase our understanding of why events have occurred and what events may happen in the future.

Following the 2008 financial crisis, the OECD (Organisation for Economic Co-operation and Development) encouraged the use of ABMs for modelling and planning economies as an alternative to the traditional mathematical based economic models (Gibson, 2011). Following this, in his work examining the fragility of the financial system, Bookstaber (2017) considered four characteristics of human interactions which again challenge the traditional mathematical model, these include *computational irreducibility* but also:

*emergence* –phenomena not programmed into a simulation which may result from the interactions of agents. Examples being flocking of birds using Reynolds’ rules (Reynolds, 1987a), or ant colony simulation (Dorigo et al., 2011).

*non-ergodicity* –unlike Newtonian physics, real-world systems, due to their inherent unpredictability, cannot be extrapolated into the future by looking at the past.

*radical-uncertainty –* events resulting in change cannot be adopted into equations because of sheer unknowability of the type of events which might occur. It would be unexpected that a modeller in the late 1940s would integrate the usefulness of the internet during a pandemic such as the 2020 COVID crisis.

If ABMs are to be considered an alternative to mathematical models, it is necessary to reiterate that they are simplified approximations of the systems they represent. If they are to be useful, then ABMs should be fully understood (de Marchi & Page, 2014).

Where systems are highly intricate, and features within the system are tightly coupled and interdependent ABMs can generate data for analysis that would otherwise be unavailable from traditional methods (Gibson, 2011). Gibson concludes that the scaled-down nature of ABMs helps to develop a better understanding of the dynamics of complex systems. Although, ABMs are themselves complex, as de Marchi (2014) explains, ABMs are the methodology used to *explain, predict, evolve or engineer* the systems or processes they are constructed from.

A hybrid framework which merges microsimulation techniques, based on probability, with the rule based methodology of ABMs is described by Singh et al in (2016) and demonstrates how different artificial life techniques can be used to predict and analyse social policies. Penn also states that political decisions should be empirically tested and artificial life and modelling is a method for doing this - instead of relying on predictive models (Penn, 2018).

Again referring to the financial crisis, but could be just as relevant for the 2020 COVID crisis, Farmer (2009) considers the impact of how politicians are making untested decisions, *‘flying the economy by the seat of their pants*’ and states that ABMs could provide valuable insights into how government policies affect economic performance, and would help to understand how the economy would react under alternative scenarios. The COVID crisis is of course a scenario where modelling has played an important role in helping governments make decisions on how lockdowns can be safely reversed (Biggerstaff et al., 2020). A coordinated scientific response in the UK called for modellers to co-operate in finding solutions for safely restarting the economy (Cates, M. Abrahams, D. Ackland, G. Batty, 2020).

It is clear from these examples that agent based modelling is a methodology which despite having a history from the 1940’s in principle, and from the 1970’s with the advent of computer modelling (Schelling, 1971) is gaining traction as a tool for evaluating decisions and testing scenarios. Improving the understanding of ABMs therefore is necessary to continue this trend. ABMs have yet to reach their potential (Richiardi, 2015, Verburg & Overmars, 2009, Tesfatsion, 2002).

**Why resilience and stability?**

A key aim of this research will be to draw conclusions on how decision making from the bottom-up affects the stability of simulations compared to top-down decision making. An examination will be made of *self-adapting* agents (bottom up) and *system-adapting* (top-down) and how these affect the stability and resilience of a simulated model. There is, outside of the ABM field, a growing interest in the properties and opportunities of bottom-up simulation (Turrell, 2016).

### A definition of stability and resilience

It is common in related research to define stability and resilience, and in this work relatively simple definitions are considered. Stability is the variance in a system; how much it changes over time, especially over a short period. For example, in terms of pricing, if the price of a good changes frequently this is less stable than a price (generated by a different mode of simulation) which is less variant. Stability will be measured using the standard mathematical v*ariance* equation along with the *mean*, as well as observations of graphed visualisations of recorded parameters. For this work, the specific quantity of variance is less important than the comparative level of variance between two simulation modes. It is also worth noting that a measurement may have variance but be predictable (for example, seasonal commodity prices), or unpredictable (prices which exhibit the properties of a random walk). Predictable variance can of course be considered stable, and so variance does not necessarily measure unpredictability in this sense. In this work however there are no intended cyclic measures and so variance is the measure of stability used. Further work could use additional statistical testing to measure the unpredictability nature of measured values which would offer further insight into the unpredictable nature of both self- and system-adaptive simulations.

Resilience is defined here as the capacity of a simulation to respond to change and recover from a disruptive event. Part of this work will simulate a disruptive event, and the resilience of a simulation will be to what extent it changes in state (by how much a measured variable is affected), and how the simulation then recovers from that disruptive event. A *recovery* is defined as the system returning to the given state prior to the disruptive event, with a similar level of variance too. Rather than measuring this in the form of a variable, resilience will be observed from charts, and again is a relative measure, with the resilience compared between the two simulation modes.

The goal of understanding and exploring measures of stability in the general area of ABMs has been highlighted as research requiring further exploration (Lee et al., 1998)(Lu & Li, 2020) although it is perhaps more common to see the subject explored in relation to a specific economic model, for example Popoyan considers it in macroeconomic models (Popoyan et al., 2017).

Stability is also a concept commonly explored in ecology (Holling & Meffe, 1996) and economics (Minsky, 1992), and therefore understanding how it can be achieved in simulation will be of interest to a wide variety of fields. There is active research in how resilience is achieved in complex systems, and many authors call for further work into this area (Dressler et al., 2019; Fraccascia et al., 2018; Schlüter & Pahl-Wostl, 2007; Singh et al., 2016; van Voorn et al., 2019). Schlüter (Schlüter & Pahl-Wostl, 2007) who discusses resilience as the capacity to cope with change, states that little has been done to analyse what properties and methods makes a system resilient.

Understanding *adaptive functions*, and the different ways they can be designed (i.e. from a system / global level, or from the individual agent level) will help modellers build models which self-regulate and produce an equilibrium of states. When disruptive events occur, those which might or might not be deliberately simulated, building stability and resilience into a model will help both the modeller and their collaborating partners - biologists, economists, sociologists – learn how the disruptive events occur, and how to respond to them.

Existing work has observed the effect that simulation rules of functions have on stability and resilience. One observation (Leal & Napoletano, 2019) finds that functions for limiting instability in trading simulations also reduce resilience, hindering recovery from a crash. Minsky (1992) states that stable regulated financial systems lead to instable financial systems, as borrowers in a financial system gain confidence, they take on more risk, producing instability and reducing resilience. The solution Minsky argues is to change the type of regulation and financial stimulation to reduce the dependency on borrowing. Minsky ultimately called for a *simpler financial system*, which suggests that resilience might be achieved with less system-wide rules and individual led behaviour in models.

Similarly, Holling (1996) argues that the management and exploitation of an ecological service (such as timber production) creates a cycle where a dependence on stability is achieved by reducing the variability in an ecosystem (or factors which could result in variability of production), but in turn leads to the declining ability of the system to self-regulate and recover from disruptive events. "If natural levels of variation in system behavior are reduced through command‐and‐control, then the system becomes less resilient to external perturbations, resulting in crises and surprises."

The research presented by these authors argue that the oversight and management of a system, whether it be an ecological or financial one, leads to stability at the expense of resilience. The modeller may be motivated by the opposing stance: what behavioural complexity could be added to a model to make it more resilient? With artificial life models it is the rules which provide resilience through emergent behaviour, so why is there a contradiction in how resilience is observed in such simple simulations and the reduction in resilience through regulation theorised in more complex systems? Chen et al (2019) concludes that the results of a model of land use show that "resilience is not a generic system property, but strongly depends on what system function is considered".

Where resilience in ABMs has been researched (Pumpuni-Lenss et al., 2017), methods were employed at the system level to restore the system from disruptive events. In the experiments in this work however, stability and resilience will be obtained from *bottom-up* behaviour – self regulation at an agent level will respond to the environment and produce cumulative change at the global system level.

# Methodology

## Model Overview

An ABM of a market-based economy has been developed. Agents both produce and sell products, and purchase and consume products of different types. The simulation is run in one of two states, one state with a *self-adaptive function*: a function which allows agents to make changes to their individual behaviour, given their individual circumstances; and another state where function behaviour is uniform to all agents – a *system-adaptive function*. These states subscribe to the bottom-up versus top-down approach of agent based modelling (Turrell, 2016).

A series of simulations will be run which attempt to answer the following questions, in each case the question is asked in respect to a comparison between simulations run for both states:

* To what degree does a simulation with a self-adaptive function display stability and resilience?
* How does a simulation with a self-adaptive function respond to disruptive events?

Two unique experiments are recorded. Each experiment is run over several discrete time intervals referred to as *days*. During each day, agents consume and produce goods, then buy and sell these in a daily auction.

The purpose of *experiment 1* is to record the simulation without any disruptive events, and to compare the stability for each adaptive function. Further measurements are taken to understand and explain the results.

*Experiment 2* measures whether the comparison in stability observed in experiment 1 is maintained during a disruptive event, and whether the model returns to its prior state.

## Simulation Design

This report refers to a model as the design of a system, and the simulation as the programmed and executed instance of the model.

The model in this research was inspired partly by an economic model designed by Steiglitz (2000). Although an economic model is the context for this work, the aim is more generalist, and further work could consider aspects of this work applied to other models, such as ecological management, for example. The model described by Steiglitz includes speculators who do not produce goods but bid for goods, in an auction, created by producers. The model in this work considers all agents as both consumers and producers representing a more integrated ecosystem with fully coupled feedback based on the need to set prices for production and to maintain consumption.

The simulation framework is programmed in object-oriented C++ code.

The simulation is turn-based and written with a single-threaded context. Future development could include a multi-threaded approach and exploitation of the GPU (graphical processing unit) where possible. Such optimisations would be especially necessary where larger scale simulations with many more agents are required.



Figure 1 Agent structure and principle behaviour

The model consists of a market-based economy made up of interacting agents (Figure 1). Agents are both consumers and producers, they strive to survive and profit. Agents are assigned one of ten occupations: butcher, brewer, baker and so on. The type of occupation makes no difference to the agent other than the market value for the goods that an agent produces, so a glut of one type of product (those that an occupation produces) will likely result in decreased prices, the inverse also being true with a shortage of a product. The purpose of the varying occupations is not to study whether one occupation outperforms another, but to enable a complex, competing economy of suppliers, where one type of good (e.g. bread) might be rising in price when another is decreasing (e.g. beer). In this case bakers might have the capital to purchase beer, but brewers (with less money) might be less willing to buy bread, and so the economy changes over time.

### Agent Properties

Agents have several properties which determine their behaviour during each day cycle and are detailed in Table 1.

|  |  |  |
| --- | --- | --- |
| **Agent Property** | **Detail** | **Representation** |
| Money | Money made from selling goods, reduced by the purchase of goods to consume | A continuous uncapped value |
| Consumption | During each day an agent will consume a fixed amount of each good they have in store. This value will affect the buy and sell pricing in the self-adaptive simulation mode.  | A value between 0 and 1. 1 is 100% consumption |
| Productivity | Represents the productivity of agents and is set randomly to between 80-100% for each agent. Affects the quantity of goods an agent produces each day. Each agent receives a quota of raw materials, and this is multiplied by productivity to produce output. The variable level of productivity is to enable a uniqueness between individual agents of a similar occupation. | A value between 0 and 1. 1 is 100% productivity |
| Satisfaction | Subjective Income Rank (Boyce et al., 2010) A measurement of how much the agent earned during the previous day in comparison to all other agents.  | A value between 0 and 1. 1 is 100% satisfaction |
| Stores to consume | A total amount of each good the agent purchases. An agent may continue to purchase goods even when there is a surplus. An agent will attempt to buy an amount of each type of good, other than the one they produce themselves.  | A continuous uncapped value |
| Stores to sell | The total amount of goods the agent has to sell. The type of good depends on the type of agent employment.  | A continuous uncapped value |
| Employment Type | Each agent has an employment type (e.g. baker, butcher, etc). This employment type defines what type of good an agent produces. An agent will consume all other type of goods.  | An identifier from 1 to 10 – each representing a different profession |

Table 1 Agent Properties and value representations

### The Daily Routine

Figure 2 illustrates the daily routine of an agent. Each agent in any given day does the following once:

1. Produce goods based on their *productivity* and the available raw materials (see Table 1). During the normal process each agent is given the same number of raw materials to produce goods. This is multiplied by the productivity. During a disruptive event, the amount of raw materials is reduced (see *Disruptive Event*, below)
2. If the self-adaptive simulation mode is active, each agent calculates a sell price for their product and a buy price for each other product. These prices are based on their individual stores of goods and agent consumption. If the system-adaptive mode is active, a single (global) buy and sell price has already been calculated for each different type of product, and passed to each agent at this point. The buy and sell prices are the fundamental factor in the self-adaptive and system-adaptive functions. (see *self-adaptive / system-adaptive functions*, below)
3. Joins an auction with all other agents to buy goods for consumption and sell produced goods.
4. Following the auction, agents will consume an amount of each product they have in store.



Figure 2 Turn based process for agents during a single day

### The Auction

During each turn, an auction is held where agents will attempt to purchase good types from selling agents. Agents are ordered into those who are prepared to pay the highest price first, and these agents get the first pick of available goods. Where an agent has a buy price greater or equal to the sell price of a selling agent, and the available capital, a transaction occurs with the final selling price being the midpoint between the buy and sell price. If an agent sells an item, that agent will immediately recalculate a selling price to accommodate demand – although this only happens in the self-adaptive simulation mode, as the system-adaptive simulation sets prices globally. It is possible that agents may not be able to buy or sell if there is a disparity in pricing, or goods are not available.

### Buying and Selling Prices

The calculation for agent sell and buy prices is derived from the bid utility function described by Steiglitz (2000) and has the following properties for bidding prices (a bid refers to both a selling and buying price):

* A bid is determined from the yesterday’s bid price multiplied by the utility function.
* The utility function depends on money and goods inventories – goods to sell in the case of the selling bid, and goods to consume for the buying bid.
* A critical parameter in the function is the desired stores of goods - the amount of goods an agent wishes to retain in their inventory. These can be goods to sell: and thus having a backlog to sell when production drops, and goods to consume: a store during periods when the agent cannot afford food. The desired store value is affected by existing stores, the current consumption of the agent (how much they are eating) and the amount of money they have.
* Bids decrease for *buying* and *selling* when good stores are high – there is less incentive to buy when good stores are high, and an agent can sell a higher quantity at a lower price and receive enough income to survive.
* Bids increase for *buying* when money levels are high – a richer agent can spend more to get the goods they require. Bids decrease for *selling* as a poorer agent has a more urgent need for money to buy goods to consume.

Figure 3 shows the effect on buy and sell prices with varying levels of money reserves and good stores.

Figure 3 Buy and Sell Price versus Food Inventory. Note the Good Stores range is greater on the Sell Price chart to show the full extent of the price / utility function.

### Experiment duration

Experiments 1 and 2 are for 1000 simulated days, this adequately demonstrates the differences in the two approaches.

|  |  |
| --- | --- |
| Experiment  | Simulation (two simulation runs – each with either a self or system-adaptive function) |
| 1 | Time period: 1000 *days.*  |
| 2 | Time period: 1000 *days*. Disruptive event at day 350, length 125 days |

Table 2 Time periods of conducted experiments.

### Self Adaptive / System Adaptive Functions

The self-adaptive function and the system-adaptive function are the principal difference between the two simulation states and represent the bottom-up versus top-down approach of decision making and agent response to the environment. Both algorithms are a function of the current money reserves and the goods inventory as described previously.

The system-adaptive function sets the buy and sell prices which all agents adopt – a single global buy price and a single global sell price for bread, for example. The average goods (food stores), and average money of all agents is used to set the buy price. The average amount of stock (goods to sell) is used to set the sell price. Once the system buy and sell price is set for each item, each agent is given the list of prices. This process occurs once each day.

The self-adaptive function is critically different to the system-adaptive function. The *individual* agent consumption and money values are used to calculate a unique buy price for each agent. Lower consumption and higher money levels will lead to a higher buy price. Similarly, the sell price is calculated from individual agent consumption and good stores. Lower consumption and lower stores lead to a higher sell price. These assumptions are based on both the Steiglitz buy and sell price formulae, and the intuitive behaviour that agents will change their buy and sell prices to increase consumption.

The self-adaptive behaviour subscribes to the *artificial life* principle ofself-autonomy. It is therefore hypothesised that a greater autonomy of agents will lead to greater stability during both the normal simulation and the periodical disruptive events during a simulation period.

## Recorded Measurements

The development of the simulation has been designed to record several agent attributes. Measurements are made for each agent once per day. The simulation then records the average value of each measurement for all agents for each occupation. These values are then averaged to provide a sample for all occupations, providing an overview for the economy for each day.

Table 3 represents each recorded value and its role within the economy.

|  |  |  |
| --- | --- | --- |
| Measurement | Detail | Representation |
| Satisfaction | See Table 1 | See Table 1 |
| Consumption | See Table 1 | See Table 1 |
| Prices | The average selling price for a product across all agents of an occupation | A continuous uncapped value |
| Stocks | Stock ready to sell for a product across all agents of an occupation | A continuous uncapped value |
| Price Change | The sum of the change in selling price across all agents for an occupation, representing the velocity of change. Measured in *experiment 1.* | A continuous uncapped value |

Table 3 Simulation Measurements

## Disruptive event

*Experiment 2* is affected by a disruptive event. Using an agent based model to simulate the effect of a disruptive event (a specific instance of a disturbance) has been detailed previously (Hoffa & Pawlewski, 2014; Van Dyke Parunak et al., 1998). Both papers simulate a disturbance in the supply chain, and specifically with Van Dyke, a comparison is made between agent-based models and equation-based models. This model adopts a similar approach to test the stability and resilience of the self- / system-adaptive modes. The event has been designed to affect the entire economy over a period and specifically reduces the available raw materials to each occupation. During a disruption, the amount of available raw materials is reduced by a random value between 75 and 100% for each occupation and is recalculated each day. The value was calibrated to have a significant enough effect for either simulation mode, and abstractly represents disruptions which might be caused by industrial action or global supply chain shortages. The disruptive event is an abstract methodology to express how agent-based models may be affected by disturbances and is not in itself a true measure or comparable to real world events. The event is simulated for a specific period of days, after which the simulation (in experiment 2) was expected to recover. The event was expected to cause volatility in production and consumption by agents, with the purpose of understanding how the self- and system-adaptive models differ in their response.

# Results

## Experiment 1 Comparison of simulation results without disruptive events.

As shown in Figure 4 the simulation initially develops through a phase of stabilisation, demonstrating that both self- and system-adaptive simulations self-calibrate prices though some variance remains.

Figure 4 Price measurements during the simulation stabilisation period up to day 50

In subsequent simulation data, the phase of stabilisation is not recorded to ensure variance is only recorded on the post-stabilisation simulation phase. Planned disruptive events also occur after this period.

As is evident in Figure 5, satisfaction, pricing and consumption measurements are more stable with the self-adaptive function. This observation of stablity continues across the measurements of variance shown in Table 4.

While the adaptive function regulates for both system and self-adaptive states, the self-adaptive function is more successful in regulating the agent buy and sell price. A stable stock level would mean regular access to each type of product, leading to greater (and more stable) consumption.

Figure 5 Satisfaction, Consumption, Prices, and Stocks for system and self-adaptive states

|  |  |  |  |
| --- | --- | --- | --- |
| Measurement |  | System-Adaptive | Self-Adaptive |
| Satisfaction | VarianceMean | 0.0029230.363635 | 0.0003360.416793 |
| Consumption | VarianceMean | 0.0001630.400451 | 0.0000260.401731 |
| Prices | VarianceMean | 0.0020754.163586 | 0.0001776.385345 |
| Stocks | VarianceMean | 202.2954424.8918 | 5.4267413.2873 |

Table 4 Comparison of variance for system and self-adaptive states during Experiment 1

The results for experiment 1, as illustrated in Figure 5 and Table 4 show that the variance (a measure of stability) is less in each measurement taken for the self-adaptive simulation. As the system-adaptive simulation sets a global sell and buy price for each good item, it may be expected that this would result in less, not more variance compared to the self-adaptive simulations – which sets buy and sell prices for goods based on an agent’s individual state. The result however is the opposite. It will help to understand what happens if agents don't have individual control over their prices.

The system-adaptive simulation attempts to set the price from the average state of all agents, but this does not cater to agents, either individually or a smaller subset of an occupational group of agents, which may collectively need the opposite action. For example, with a product sell price, if overall stocks of a particular type are high, the system will decrease the selling price. A sub-set of agents may have low stocks however, in which case the price is largely incorrect. In this scenario the lower goods price will encourage more sales without the regulation of higher prices to counteract scarcity. Without this counteraction, the number of agents (within an occupation) with lower stocks will continue to increase, eventually outnumbering those with higher stock levels and triggering a reverse effect (allowing the system to increase the price). A seesaw of price increases and decreases will occur, across occupations throughout the simulation, resulting in the variance.

It may also help to see the velocity of price changes – i.e., the rate at which the goods prices change each day, calculated as average difference in price each day for each agent for the goods item they sell.

Figure 6 Difference in sell price changes per day for self and system-adaptive simulations

Figure 6 demonstrates that the self-adaptive simulation, which allows agents to tailor buy and sell prices for their individual needs, is busier when it comes to changing sell prices. There is an average price change of 0.33 for the self-adaptive simulation compared to 0.05 for the system-adaptive simulation. The difference is always positive, so a sell price change of 0.33, for example, might be an upward or downward swing in price. Examining the pricing in Figure 5, and observing the relatively low variance for the self-adaptive simulation, there is an apparent contradiction to the higher rate of change observed here. As the change in price is always positive, this hides the fact that agent prices could in fact be, when the average price is calculated, cancelling each other out. The result of each agent being able to calibrate their prices on an individual basis is an overall more stable average price, the opposite being the case for the system adaptive simulations. In summary, having the ability to work harder to change prices, self-adaptive agents achieve the lower overall variance, or stability, compared with the system-adaptive. Externally the self-adaptive simulation is calm, but internally it works harder to achieve this.

## Experiment 2

Experiment 2 runs both simulations with a disruptive event – the variable reduction in the supply of raw materials needed to produce goods. The event occurs for 125 simulated days.

Figure 7 Prices, Stocks and Satisfaction and Consumption during a 125-day disruptive event for system and self-adaptive states

|  |  |  |  |
| --- | --- | --- | --- |
| Measurement |  | System-Adaptive | Self-Adaptive |
| Prices | VarianceMean | 0.1888794.057122 | 0.0077966.422076 |
| Stocks | VarianceMean | 4260.241424.7720 | 2047.142392.8933 |
| Satisfaction | VarianceMean | 0.0017990.307964 | 0.0030800.412704 |
| Consumption | VarianceMean | 0.0029530.382459 | 0.0025840.382566 |

Table 5 Comparison of variance system and self-adaptive states during Experiment 2

As can be seen in Figure 7 and Table 5 the disruptive event affects both simulations but differs compared to the measurement taken. The effect it has on prices is greater for the system-adaptive than the self-adaptive, is similar for consumption and stocks, and has a greater effect on the self-adaptive simulation for agent satisfaction.

One further observation is that for all measurements there is an apparent increase in variance after the disruption for the system-adaptive simulation, but not the self-adaptive. To confirm whether this was always the case, and not just an observation more apparent in this particular simulation, 10 further simulation runs in the system-adaptive mode were recorded with and without the disruption, and the measurement of variance was taken from time period 600 to 1000 – the time after the disruption. This demonstrated a mean variance of 989.39 for simulations with disruption (measuring stock levels), compared to 675.85 to simulations without a disruption, indicating that the disruption was the cause for the increased post-disruption variance.

In terms of the self- versus system-adaptive simulations, this demonstrates that the self-adaptive simulation recovers and maintains its state post-disruption. As shown in experiment 1, the self-adaptive works harder, at the agent level, to set prices appropriate to stock levels. The disruption clearly would affect the self-adaptive, but at least in terms of prices the effect it has is less. In relation to the increase in variance seen after the disruption in the system-adaptive simulation, this requires further analysis. It is speculated that the disruption causes an increase in the ‘bad’ pricing which is not completely resolved after the disruption ends. It is also speculated that the increase in variance is not just caused but enhanced by the disruption, i.e., it would eventually occur, but the disruption facilitates this sooner. The proof of this speculation requires further work and may help modellers understand how some measurements recover from system instabilities.

### Recognition of Primary and Secondary Measurements

It can also be seen in Table 5 that the effect of the disruption varies for the self-adaptive simulation, in comparison to the system-adaptive simulation, depending on the measurement taken. The agent pricing function (in both system and self-adaptive states) principally serves to set the appropriate price for goods, and so it is expected that one simulation type will perform better at limiting a change in prices. The other measurements, c*onsumption,* *satisfaction,* and *stocks*, although clearly affected by the agent pricing, as seen in experiment 1, are less coupled. So although Table 5 shows that overall the variance is still less over the entirety of the simulation, Figure 7, demonstrates a different overall response during the disruption. A distinction can therefore be made between *primary* (first order) variables, those which are directly regulated by pricing function, and *secondary* (second order), those which are not. *Price* can be considered in this scenario to be a primary variable and c*onsumption,* *satisfaction,* and *stocks* secondary variables.

## Model Plausibility

The model is an attempt to understand the general, generic behaviour of an ABM with the context of a market-based economy. Do the results and observations match those found in the real-world? The results of the simulations show that the bottom-up (self-adaptive) model to be more stable during periods where is no disruption. Mahmoodi (2018) observes that a bottom-up self-organising model to be more resilient than a top-down model, which in their experiments tends to collapse. Additional work on the observation and causes of the occurring instability seen in the system-adaptive simulation could help to associate this further.

Another comparison of the resulting stability in self-adaptive decision-making can be made when reviewing Ratner (2020). In their work it is argued that a systematically weakening of the collective bargaining power of workers (and so a more adaptive, self-organised approach), has reduced inflation volatility since the 1980s.

During periods of crisis governments tend to act with more control, for example during the Second World War, the Great Recession and the COVID crisis. The model could be expanded to mix the two adaptivity methods – this is considered for future work in the Conclusion below.

The model here allows agents in the self-adaptive scenario to adjust their pricing with more sensitivity and thus the system reacts and adapts more quickly than the system-adaptive scenario. Keynes (1936) also argued that when wages do not fall in a recession, an economy would be slower to adapt.

# Conclusion

The aim of this work was to demonstrate whether simulations which rely on agents making their own decisions could be more stable than those which have such decisions made at the global (or system) level. The economic context was useful to provide a basis for building a model, rather than using abstract measurements, but at the same time it wasn’t intended for economists to draw deep conclusions on the results of the model in comparison to real-world scenarios – although it may be of use with further design.

The results from the self-adaptive simulation appear to be more stable and settled over the course of the simulations. It may initially be expected that a system which sets a global buy and sell price would be more settled, as there is a globally constant value, but this does not reflect the results seen here. Agents which can cater for their own needs, rather than that of the majority of their neighbours, in this case produce a more stable less chaotic simulation.

The research set out to answer two questions: how measurements of stability compare during simulations when agents can adapt with more self-interest to their environment (bottom up versus top down); and secondly, how simulations of these two adaptive states respond to disruptive events. Stability is defined as a measure of variance and resilience is the impact a disruptive event has on measured variables, and whether the simulation recovers to its prior state once the disruptive event has ended.

The first experiment, a comparison of the two states with no disruptive event, observed the self-adaptive function being more stable for all variables, an observation which initially suggests that self-regulation is comparatively more stable.

The second experiment measured the effect of a single disruptive event. It found that the self-adaptive simulations responded variably in comparison, but also saw the observation that the recovering state was more predictable (returning to its prior state), whereas the system-adaptive simulations tended to see an increase in variance after a disruption. Where variance, compared between the two simulation states differed, it was identified that variables could be primary, (first order) variables to the adaptive function, or secondary (second order). Testing this hypothesis of primary and secondary variables could be a consideration for future work when measuring stability. Further amendments to this experiment may also offer an insight into the effect of short and long-term disruptions, for example comparing the long-term disruption of the COVID pandemic and the shorter 2008 economic crisis with the 125-day disruption and potentially longer simulated disruptions and recovery periods.

It has been useful to measure the activation, or velocity, of variables. Measuring this had provides an insight into the sensitivity of change to an event and could be used in further work to understand how ‘internal’ changes cause quite different ‘external’ observations.

The self-adaptive function improved the resilience of the primary variables: would additional self-adaptive functions, those regulating other variables, improve the stability of the system further, or would these functions work against each other? Reynold's (1987a) flocking rules: separation, alignment and cohesion result in a new state of emergent behaviour, despite being in contradiction to each other, suggesting that a further increase in stability could be a consequence.

How do simulations respond when a self-adaptive function is de-activated? What if the self-adaptive function is switched to a system-adaptive function during a disruption? Could it reduce the effect of instability on secondary measurements?

Is there a function which can reduce the impact of instability during state changes? Finding such a function could build on work by Pumpuni-Lenss (2017) which assesses strategies to restore stability to a system.

Powers (2018) determines the rules that support cooperation between groups, which, in the light of this work, raises the question on how self-adaptive functions which focus entirely on self-interest compare to that of self-adaptive functions which respect cooperation and the greater health of the economy.

This work attempts to draw general conclusions from a specific economic context, and thus while the aim of the disruptive event was to simulate a disturbance in the general sense, further work would help to improve this by defining and testing a variety of classes of disturbances. Further work could also consider a more objective measure of resilience to draw more detailed insights in addition to the measure of variance used here.

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