"Agent-Based Modelling in Socio-Economic Systems"

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Introduction to Modelling and Simulation

1. **Modelling.**

   Simulation.

2. **Agent-Based Modelling.**

3. **Learning and Simulation.**

1. Modelling — from March & Lave

1.1 Overview

A. What is a model?

B. What is a good model?

A. A model:

- **a simplified picture of a part of the real world.**
- **has some of the real world's attributes, but not all.**
- **a picture simpler than reality.**

We construct models in order to explain and understand.

Three Rules of Thumb for Model Building:

- **Think "process".**
- **Develop interesting implications.**
- **Look for generality.**

Judge models using: truth, beauty, justice.

Interplay between the real world (truth), world of æsthetics (beauty), world of ethics (justice), and the model world.

Example: The firm —

Prices, Costs, and Values $\rightarrow$ ***Profits***

We use verbal, graphical, and algebraic models of how consumers, firms, and markets work.

We assume rationality: that economic actors (consumers and firms) will not consistently behave in their own worst interests.

Not a predictive model of how individuals act, but robust in aggregate.

1.2 Modelling

Speculations about human behaviour/social and organisation interactions.

Explore the arts of

- **developing**
- **elaborating**
- **contemplating**
- **testing**
- **revising**

models of behaviour.

What is a model?

- **We can have several models of the same thing, depending on which aspects we want to emphasise, how we will use the model.**

- **Models are constructs to explain and appreciate the real world.**

So ...

Need *skills* of:

- **— *abstracting* from reality**
- **— squeezing *implications* out**
- **— *evaluating* a model**

We can produce more complex behaviour than we are capable of understanding:

> **the behaviour of a baby baffles a psychologist (and vice versa)**

Q: If we cannot understand individual behaviour, then how are we to understand systemic/social/bureaucratic behaviour?

Six familiar models in the social sciences:

- **individual choice under uncertainty**
- **exchange/trade**
- **adaptation of ideas/technology**
- **diffusion of ideas/technology**
- **transition**
- **demography**

Each is treated by March & Lave (1975).

1.3 Model of the Model-Building Process

1. **Observe some facts.**
2. **Speculate about processes that might have produced such observations.**
3. **Deduce other:**
   - **results**
   - **implications**
   - **consequences**
   - **predictions**

   — from the model: "If the speculated process is correct, what else would it imply?"
4. **Are these *true*? If not, speculate on other models/processes.**

Case: Contact and Friendship.

Why are some people friends and not others?

e.g. **In a hall of residence,**
lists of friends

Observe: friends live close together.

Process?

What is a possible process that might produce the observed result?

Two Speculations about Process:

1. **previous friends chose to live together**

   $\Rightarrow$ if had lists of friends from previous year, then fewer clusters of friends, why?

   observe: friendship patterns among first, second, and third years $\rightarrow$ no difference in clusters (against expectation)

2. **friendships develop through contact and common background, given a potential for friendship**

   What changes in these friendship clusters over time?

   $\Rightarrow$ through the year a strengthening of clusters of friends

   observe this? yes.

Generalisation

We want to include earlier predictions but find a more general model that predicts new behaviours as well, more widely.

Can we generalise this?

- **beyond the university?**
- **communication → friendship?**
- **enemies as well as friends?**

e.g. 2) The professor forgets to bring the undergraduate homework to class. Why?

1.4 Three Rules of Thumb

1. *Think "process".*
   A good model is almost always a statement about a process. Many bad models fail because they have no sense of process. When you build a model, look at it for a moment and see whether it has some statement of process.

2. *Develop interesting implications.*
   Much of the *fun* in model building comes in finding interesting implications in your models. A good strategy for producing interesting predictions: look for natural experiments.

3. *Look for generality.*
   Ordinarily, the more situations a model applies to, the better it is and the greater the variety of possible implications.

1.5 Evaluation of Speculative Models

I. **Truth**

II. **Beauty**

III. **Justice**

Justice:

be aware of a responsibility to society beyond the "search for truth".

Beauty:

- **Simplicity, or parsimony**
- **Fertility (many predictions/assumptions)**
- **Surprise!**

e.g. Parental preference for sons.

“Suppose that each couple agreed (knowing the relative value of things) to produce children (in the usual way) until each couple had more boys ♂ (the ones with penises) than girls ♀ (the ones without).

And further suppose that the probability of such coupling (technical term) resulting in a boy (the ones with) varies from couple to couple, but not from coupling to coupling for any one couple.

And (we still have a couple more) that no one divorces (an Irish folk tale) or sleeps around (a Scottish folk tale) without precautions (a Swedish folk tale).

And that the expected sex (technical term) of a birth if all couples are producing equally is half male ♂, half female ♀ (though mostly they are one or the other).”

Rule: “stop having kids when sons outnumber daughters”

Question: “(Are you ready?) What will be the ratio of boys (with) to girls (without) in such a society?”

A Surprise —

→ **for *most couples*: more sons than daughters.**

but —

for *society*: more girls than boys,

Let’s simulate this using NetLogo:

http://www.agsm.edu.au/~bobm/teaching/SimSS/NetLogo-models/boysngirls.html

Truth:

- **correct (or more correct) models**
- **requires clever, responsible detective work to find the truth**
  (aim for objectivity, but face subjectivity if it exists)
- **test implications, not assumptions**
- **predicting is not equivalent to understanding, necessarily**

Need *Critical Experiments:*

compare alternative models
with the same question $\longrightarrow$ different answers:
this is critical.

Beware Circular Models:

a. **“when the rain-dance ceremony is properly performed, and all the participants have pure hearts, then it will rain” — testable?**

b. **“people pursue their own self-interest”**
— don’t predict values from behaviour and then predict the same behaviour from the values just derived.

c. **Monty Python’s “the man who claims he can send bricks to sleep”**

e.g. 3). The Case of the Stupid Question

e.g. "a surfer asked a stupid question in class"

Speculations:

A. not enough time to study

B. success on the board is sufficient for her

C. jealous of her prowess at surfing, the rest of us look down on her classroom performance and interpret her questions as "stupid"

How do the Implications Differ?

	Speculation A	Speculation B	Speculation C
Q1: will athletes ask stupid questions out of season?	no	yes	yes
Q2: will athletes ask stupid questions in places that don’t emphasise althetics?	yes	no	no
Q3: will athletes who don’t look like athletes ask stupid questions?	yes	yes	no

The Importance Of Being Wrong

- **evaluate rather then defend (avoid “falling in love” with your model)**
- **delight in finding fault — be skeptical and playful**
- **always think of alternative models**

2. Simulation

Social Science, not Physical Science

At the aggregate level, similar.

But at the micro level, the agents in social science models are people, with self-conscious motivations and actions.

Beware: Aggregate behaviour may be well described by differential equations, with little difference from models of inanimate agents at the micro level.

The Five Functions of Simulations:

(from Hartmann 1996)

1. **As a Technique — to investigate the detailed dynamics of a system.**
2. **As a Heuristic Tool — to develop hypotheses, models, and theories.**
3. **As "Experiments" — perform numerical experiments, Monte Carlo probabilistic sampling.**
4. **As a Tool for Experimentalists — to support experiments.**
5. **As a Pedagogic Tool — to gain understanding of a process.**

1. As a Technique

- **Solution of a set of equations describing a complex (e.g. bottom-up) interaction.**
- ***Discrete* (Cellular Automata): if the model behaviour ≠ empirical, it must be because of the transition rules.**
- ***Continuous*: not so clear-cut: background theory v. model assumptions**

  Q: does more realistic assumption → more accurate prediction?

"A simulation is no better than the assumptions built into it" — Herbert Simon

2. As a Heuristic Tool

Simulation is useful where the theory is not well developed, and the causal relationships are not well understood:

- **theory development = guessing suitable assumptions that may imitate the change process itself;**

- **but how to assess assumptions independently?**

Steve Durlauf: Is there an underlying optimisation by agents? (his "Complexity and Empirical Economics," ***EJ*****, 2005)**

3. As a Substitute for Experiment

When actual experiments are perhaps:

- ***pragmatically*** **impossible: scale, time; or**
- ***theoretically*** **impossible: counterfactuals; or**
- ***ethically*** **impossible: e.g. taxation, no minimum wage;**

or **to complement lab experiments**

e.g. Agent-Based Models v. Economic Experiments

Hailu & Schilizzi (2004, p.155) compare and contrast ABMs with experiments using human subjects, under the headings:

- **Approach to inference, or micro-macro relationship**
- **Specification of behavioural rules**
- **Informational problems**
- **Degree of control**
- **Explanation of agents' choices**
- **Temporal length of analysis**
- **Representativeness / realism**
- **Data**
- **Cost**

4. As a Tool for Experimentalists

- **to inspire experiments**
- **to preselect possible systems & set-ups**
- **to analyse experiments (statistical adjustment of data)**

5. For Learning

A pedagogic device through play ...

See Mitchell Resnick. *Turtles, termites, and traffic jams: Explorations in massively parallel microworlds*. MIT Press, 1994.

Play with NetLogo models, and experience emergence: Life is famous, and others too.

Summary

A simulation imitates one process by another process

With Social Sciences: few good descriptions of static aspects, and even fewer of dynamic aspects
(Remember: existence, uniqueness, stability)

Robust Predictions from Simple Theory

(from Latané, 1996)

Four conceptions of simulation as a tool for doing social science:

1. **As a scientific tool: theory + simulation + experimentation**
2. **As a language for expressing theory:**
   - **natural language,**
   - **mathematical equations (i.e., closed form), and**
   - **computer programs, such as C++, Java, etc.**
3. **As an "easy" alternative to thinking: robust coding**
4. **As a machine for discovering consequences of theory: if this, then that.**

A Third Way of Doing Science DIS

(from Axelrod & Tesfatsion 2006)

Deduction + Induction + Simulation.

- **Deduction: deriving theorems from assumptions**
- **Induction: finding patters in empirical data**
- **Simulation: assumptions → data for inductive analysis**

S differs from D & I in its implementation & goals.

S permits increased understanding of systems through controlled computer experiments

Emergence of self-organisation

Examples: ice, magnetism, money, markets, civil society, prices, segregation.

Defn: emergent properties are properties of a system that exist at a higher level of aggregation than the original description of the system.
Not from superposition, but from interaction at the micro level.

Adam Smith's Invisible Hand → prices

Schelling's residential tipping (segregation) model:
People move because of a weak preference for a neighbourhood that has at least 33% of those adjoining the same (colour, race, whatever) → segregation.

Need models with more than one level to explore emergent phenomena.

Families of Simulation Models

1. **System Dynamics SD**
   (from differential equations)
2. **Cellular Automata CA**
   (from von Neumann & Ulam, related to Game Theory)
3. **Multi-Agent Models MAM, or Agent-Based Computational Economics ACE, or Agent-Based Models ABM, or Multi-Agent Systems MAS**
   (from Artificial Intelligence)
4. **Learning Models LM**
   (from Simulated Evolution and from Psychology)

Comparison of Simulation Techniques

Gilbert & Troitzsch compare these (and others):

Technique	Number of Levels	Communication between agents	Complexity of agents	Number of agents
SD	1	No	Low	1
CA	2+	Maybe	Low	Many
MAM	2+	Yes	High	Few
LM	2+	Maybe	High	Many

Number of Levels: "2+" means the technique can model more than a single level (the individual, or the society) and the interaction between levels.

This is necessary for investigating emergent phenomena.

So "agent-based models" excludes Systems Dynamics models, but can include the others.

Simulation: The Big Questions

from: www.csse.monash.edu.au/~korb/subjects/cse467/questions.html

- **What is a simulation?**
- **What is a model?**
- **What is a theory?**
- **How do we test the validity of any of the above?**
- **When do we trust them, what sort of understanding do they afford us?**
- **What is an experiment? What does it mean to experiment with a simulation?**
- **What is the role of the computer in simulation?**
- **How does general systems dynamics influence simulations?**
- **How do we handle sensitivity to initial conditions?**
- **How precisely can a simulation approximate real life / a model?**
- **How do we decide whether to use a theory / model / simulation / lab experiment / intuition for a given problem?**
- **Does a simulation have to tell us something?**
- **How complex is too complex, how simple is too simple?**
- **How much information do we need to (a) build and (b) test a simulation?**
- **How/when can the transition from a quantitative to a qualitative claim be made?**

Verification & Validation

Verification (or internal validity): is the simulation working as you want it to:

— is it "doing the thing right?"

Validation: is the model used in the simulation correct?

— is it "doing the right thing?"

To Verify: use a suite of tests, and run them every time you change the simulation code — to verify the changes have not introduced extra bugs.

Validation

Ideally: compare the simulation output with the real world.

But:

1. ***stochastic*** **∴ complete accord is unlikely, and the distribution of differences is usually unknown**
2. ***path-dependence*****: output is sensitive to initial conditions/parameters**
3. **test for "retrodiction": reversing time in the simulation; or: test from a past date to the present: calibrate with history**
4. **what if the model is correct, but the input data are bad?**

Use Sensitivity Analysis, to ask:

- **robustness of the model to assumptions made**
- **which are the crucial initial conditions/parameters?**

use: randomised Monte Carlo, with many runs.

Judd's ideas (2006)

"Far better an approximate answer to the right question … than an exact answer to the wrong question."

— John Tukey, 1962.

That is, economists face a tradeoff between:

the numerical errors of computational work
and
the specification errors of analytically tractable models.

Judd on Validation

Several suggestions:

1. **Search for counterexamples:**
   If found, then insights into when the proposition fails to hold.
   If not found, then not proof, but strong evidence for the truth of the proposition.
2. **Sampling Methods: Monte Carlo, and quasi-Monte Carlo $\longrightarrow$ standard statistical tools to describe confidence of results.**
3. **Regression Methods: to find the "shape" of the proposition.**
4. **Replication & Generalisation: "docking" by replicating on a different platform or language, but lack of standard software an issue.**
5. **Synergies between Simulation and Conventional Theory.**

Axelrod on Model Replication and "Docking"

***Docking*: a simulation model written for one purpose is aligned or "docked" with a general purpose simulation system written for a different purpose.**

Four lessons:

1. **Not necessarily so hard.**
2. **Three kinds of replication (in decreasing closeness):**
    - a. **numerical identity**
    - b. **distributional equivalence**
    - c. **relational equivalence**
3. **Which null hypothesis? And sample size.**
4. **Minor procedural differences (e.g. sampling with or without replacement) can block replication, even at (b).**

Reasons for Errors in Model Docking

1. Ambiguity in published model descriptions.
2. Gaps in published model descriptions.
3. Errors in published model descriptions.
4. Software and/or hardware subtleties.
   e.g. different floating-point number representation.

(See Axelrod 2006.)

Validation

For whom?

With regard to what?

A good simulation is one that achieves its goals:

- **to explore**
- **to predict**
- **to explain**

Or

- **what is? (i.e. description, positive)**
- **what could be? (i.e. existence, plausibility)**
- **what should be? (i.e. prescription, normative)**

Consider historical market data:

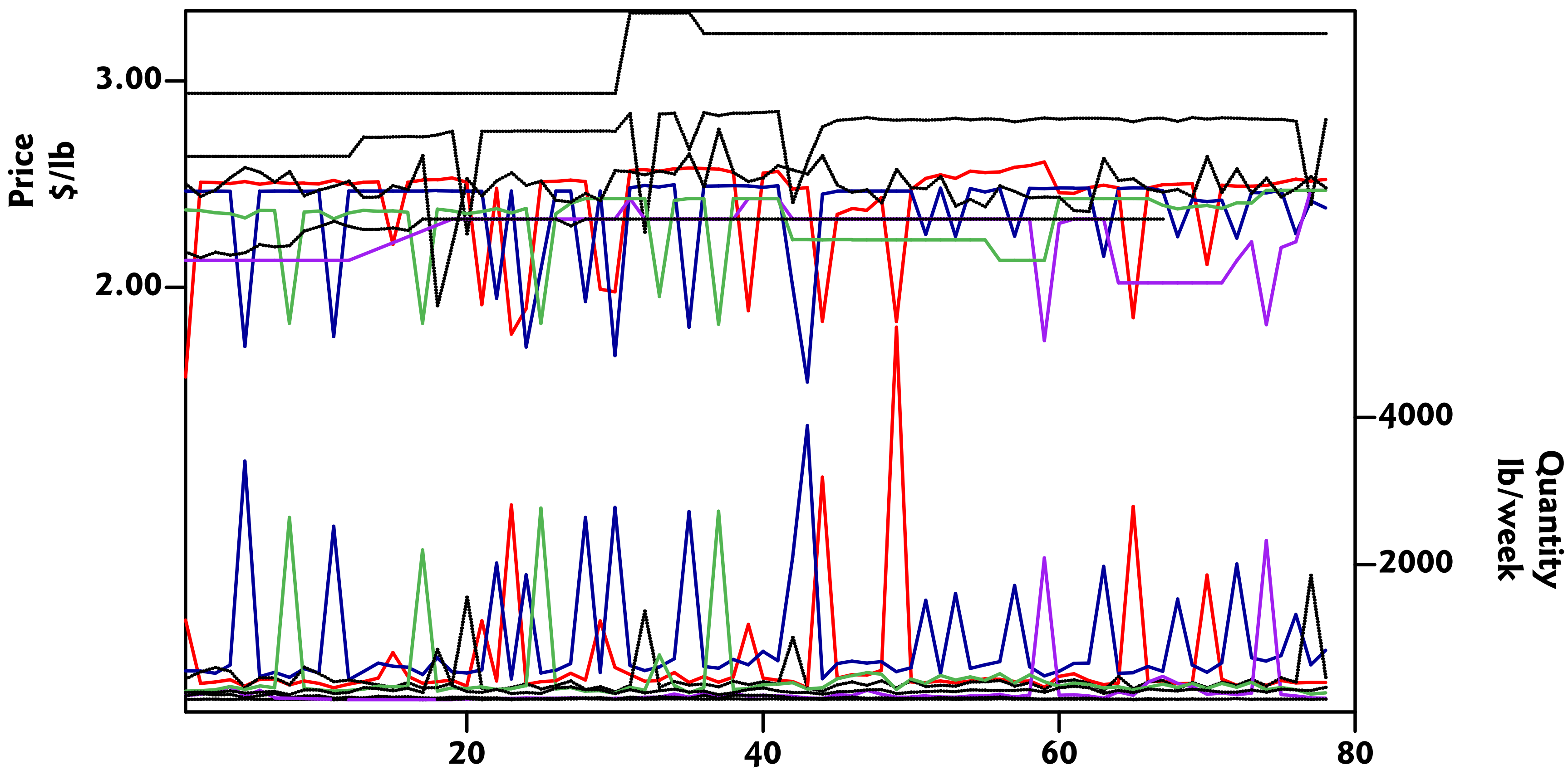

Figure 1: Weekly Prices and Sales (Source: Midgley et al. 1997)
(Coloured lines: Folgers, Maxwell House, Hills Bros, CFON)

Stylised Facts of the Market Behaviour

- **Much movement in prices and quantities of four brands — a rivalrous dance.**
- **Pattern: high price (and low quantity) punctuated by low price (and high quantity).**
- **Another four brands: stable prices and quantities**

Questions:
What is the cause of these patterns?

— **shifts in brand demand?**

— **reactions by brands?**

— **actions by the supermarket chain?**

— **unobserved marketing actions?**

Explanations?

Interactions of profit-maximising agents, plus external or internal factors → via a model → behaviour

Similar (qualitatively or quantitatively) to the brands' behaviours of pricing and sales.

Note: assuming profit-maximising (or purposeful) agents means that we are not simply curve-fitting or description using D.E.s. Going beyond the rivalrous dance.

Further ...

With a calibrated model, we can:

perform sensitivity analysis of endogenous with respect to exogenous variables.

Prediction only requires sufficiency, not necessity ("These are the *only* conditions under which the model can work.")

Examine:

- **limits of behaviour (Miller's Automated Non-linear Testing System)**
- **regime-switching**
- **range of behaviour generated**
- **sensitivity of the aggregate (or energent behaviour) to a single agent's behaviour.**

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