Agent-Based Market Design

Robert Marks

Australian Graduate School of Management
bobm@agsm.edu.au

(borrowing from Marks 2006, and Kunchamwar, Marks, & Midgley 2005)
Outline of Talk

1. Introduction
2. Analysis and Simulation
3. Learning
4. Analysis → Design
5. Market Mechanisms
6. Designing Electricity Markets
7. Designing Auctions
8. Conclusions
1. Introduction

What is “market design”? 
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When?
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When?

With the designing and implementing of new, “designer” markets.

Using ACE: Agent-based Computational Economic models.
(See the 2006 *Handbook*, ed. by Tesfatsion & Judd.)
New Designer Markets:
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2. Analysis and Simulation

1. To change, we must understand: analysis
2. Complexity calls for simulation
3. Understanding leads to improvement: design.
Closed-Form Analysis:
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1. Observation.
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Analysis, and then synthesis, or design.
Simulation and Analysis: Why Simulation?

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4. To model *learning*.
3. Learning

- GA as a model of adaptive population learning agents:
  - individuals
  - routines, ideas, heuristics
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- Implicit learning from generation to generation.
Explicit Learning

  \[ q_{ij}(t - 1) = q_{ij}(t) + (x - x_{\text{min}}) \]
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  \( \phi \): recency, \( \varepsilon \): experimentation.
  But inductive learning: not anticipative.
  

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  — individual learning of the non-GA ACE model
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- Significance of the learning model?
4. Analysis → Design

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4. Analysis → Design

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2. experimental results from economics laboratories;
3. computational exploration of different designs. “Exploration:” analysis and synthesis.
4. (and, finally, direct design — optimisation of an objective function, where possible)
**Bottom-up design:**

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Evolutionary and agent-based computation raises the possibility of bottom-up design or emergence through simulation.
Sufficiency or Necessity?

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Sufficiency or Necessity?

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Where the mapping is sufficiently well understood, and where closed-form analytic solution is possible, it should be possible to describe not only **sufficiency** — if the market has this structure, and the rules of trading are such and such and the traders are given this information, then this performance and behavior will follow, at least in general form — but also **necessity** — if you want this performance and behavior, then this is the only set of designs (combinations of structure and rules) that will produce it.
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Only if small numbers of degrees of freedom will simulation \(\rightarrow\) necessity.

e.g. DNA structure and mechanism
Marketplace Design Framework
(MacKie-Mason & Wellman, 2006)

A transaction:
1. the connection
2. the deal
3. the exchange
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The Marketplace system:
  • agents
  • market mechanism
  • embedded in an amount of social institutions
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∴ Design of:

- market mechanism  
- agents
5. Market Mechanisms

i.e. “the deal”: allowable actions $\rightarrow$ settlement
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Specify:
- which concerns of agents are recognised
- permissable rules
- rules: actions $\rightarrow$ allocations
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- permissable rules
- rules: actions $\rightarrow$ allocations

Model the constraints:

eg no external subsidies, maintain horizontal equity, etc
6. Designing Electricity Markets

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With evolution, the design would occur in the genome space, while the behavior or performance occurs in the phenome space.
Syntactic Complexity

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Mapping: initial conditions of structure and rules $\rightarrow$ behavior and performance is not smooth or continuous:
Design Trade-offs

Possible criteria for a single auction (Phelps et al., 2002, 2005):

1. maximising seller revenue
2. maximising market efficiency
3. discouraging collusion
4. discouraging predatory behaviour
5. discouraging entry-deterring behaviour
6. budget balance
7. individual rationality
8. strategy-proofness
For an electricity market:

- reliable service (no blackouts or brownouts)
- fair and open access at reasonable prices
- effective price signals: investment in generation and transmission
- effective oversight to mitigate market power.

Market power has been a focus of ACE electricity modellers, given the degrees of freedom closed-form analysis is deprecated.
Design of ACE Markets
(LeBaron, 2006)

1. economic environment & object traded
2. agent’s preferences
3. market clearing & price formation
4. the fitness measure
5. use of information
6. market learning
7. benchmarking
Use of Agents

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In finance, ACE design useful for exploring:

- stockmarkets
- microfoundations
- tick sizes
- different learning mechanisms
- etc
Early Electricity Modelling

“Arguably, a well-constructed computer model could improve the accuracy of our competitive analysis in at least two ways: by explicitly representing economic interactions between suppliers and loads at various locations on the transmission network, and by accounting for the actual transmission flows that result from power transactions.” and

“Consistency of data sources and consistent application of those data is an attraction, but such techniques require time, education, and consistent refinement. Moreover, adequate data may not be available. I hope the benefits will be worth our trouble and investment. Our economists are trying to get a handle on precisely that equation.”

— then FERC Chairman, James Hoecker, 1998.
“Single-Population GAs” v. ”Agent-based Models“

At first, research models mainly used single-population GAs: Curzon Price (1997) discussed this possibility.
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ACE models are becoming more popular than single-population GA-based models, as seen in citations in the IEEE Xplore on-line database.
Antecedents:

- Andreoni & Miller (1995)
- Wellman et al. (1998),
- Curzon Price (1997)
- Richter & Sheblé et al. (1998), (1999), (2000),
- MacGill & Kaye (1999),
- Harp (2000),
- Nicolaisen et al. (2000, 2001)
Engineers and economists:
  • The Finns.
  • Bunn and associates.
  • Tesfatsion and associates.
  • Computer scientists.

Early users of ACE methods
The Finns


1995: agent-based modelling framework

1997: a von Stackelberg market; maximising market efficiency (sum of buyers’ and sellers’ surplus); both sides as agents
Tesefsion and associates

Two influential papers (2000 & 2001):
Both use discriminatory-price clearinghouse \( k \)-DA
Both focus on market power
Both assume sellers seek to max their profits

Compare GA learning and RL
Tesfatsion and associates

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Both use discriminatory-price clearinghouse \( k \)-DA
Both focus on market power
Both assume sellers seek to max their profits

Compare GA learning and RL

Found that RL produced better results (higher efficiency) than did single-population GAs, due to extra-market social learning (Vriend).
Bunn and associates


Higher prices with discriminatory.

2003: what market conditions sufficient for exercise of market power? Used RL. Agents can price and withhold capacity.
Recent Studies

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“important comparisons were made with theoretical results and documented economic experiments with human subjects in order to ensure reasonable behavior of the agent-based simulations.
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“configured the agents in an attempt to eliminate experimental bias. First, the demand players always bid their willingness-to-pay: price takers. The suppliers exercise all of the strategy in our simulation, and each one uses an identical strategy of aggressive profit maximization.
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“marginal suppliers utilize a very simple naïve rule as a greedy algorithm for rent capture: test the margin by raising their bid prices.”
7. A Synthetic Auction Design

Byde (2002): A auction where the highest bidder wins and pays an amount given by

$$(1 - w)bid_1 + wbid_2,$$

where $bid_1$ is the highest (sealed) bid and $bid_2$ the second-highest.
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Found under certain plausible conditions that seller’s revenue is maximised when \(w = 0.3\), a synthetic auction superior to both first-price and second-price auctions.
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Possible reasons:

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ii. estimation of the simulation model

iii. I would add:
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Possible reasons:

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ii. estimation of the simulation model

iii. I would add: in general, *no necessary conditions* from simulation, *just sufficient conditions*

iv. and validation of the model.

(but also applies to closed-form models)
Validation

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- Verification: model does what modeller wants.
  Validation: model is accurate and appropriate.
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• But: Solving the equations right, versus Solving the right equations.

• Verification: model does what modeller wants. Validation: model is accurate and appropriate.

• Model ↔ Theory ↔ Phenomenon
Validation is difficult

- Especially a model of a complex system (with emergence). (Kelton et al. 2001)
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- Especially a model of a complex system (with emergence). (Kelton et al. 2001)
- A large parameter space. (Shervais et al. 2003)
- Path dependence, positive feedback, extreme sensitivity to initial conditions.
- Little knowledge of micro-details.
LeBaron (2006)’s steps

- Replicate difficult empirical features: do ACE models fit facts not otherwise explained?
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- Put parameters under evolutionary control: learning rates, memory depth.
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• Replicate difficult empirical features: do ACE models fit facts not otherwise explained?

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• Use results from lab experimental markets: learning dynamics for ACE models.
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- Use results from lab experimental markets: learning dynamics for ACE models.

ACE modellers try harder:
LeBaron (2006)’s steps

- Replicate difficult empirical features: do ACE models fit facts not otherwise explained?
- Put parameters under evolutionary control: learning rates, memory depth.
- Use results from lab experimental markets: learning dynamics for ACE models.

ACE modellers try harder: the challenge of validation to gain acceptance is an opportunity to demonstrate the relative indifference of the closed-form traditionalists to validation.
How to Validate

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• benchmarking: against history, against other models;

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• looking at the model as a “black box” and exploring its response to step functions (off & on, min & max, one input variable at a time),
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• looking at the model as a “black box” and exploring its response to step functions (off & on, min & max, one input variable at a time),

• statistically estimating the model as a function from inputs to outputs (inputs as independent vars, outputs as dependent vars).
First convince oneself

Judgement of modeller → acceptance of policy-makers?

Modeller should convince herself, as the most skeptical observer. Lawyers?
Conclusions
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So: Why ACE?

• Explanation, using bottom-up modelling.
• Occam’s Razor: trade-off between simplicity and encompassing reality.

But reality might be simpler than theory suggests.
Conclusions

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So: Why ACE?

• Explanation, using bottom-up modelling.
• Occam’s Razor: trade-off between simplicity and encompassing reality. But reality might be simpler than theory suggests.
• Validation: We try harder!