Modelling of Complex Systems

25th Nov 2009

Dr Liz Varga
liz.varga@cranfield.ac.uk

Cranfield UNIVERSITY

- Director of Complex Systems Research Centre
- PhD thesis: coevolution of the firm and the supply network
- BA(Hons) Pure Maths & Data Analysis; MBA (Cranfield)

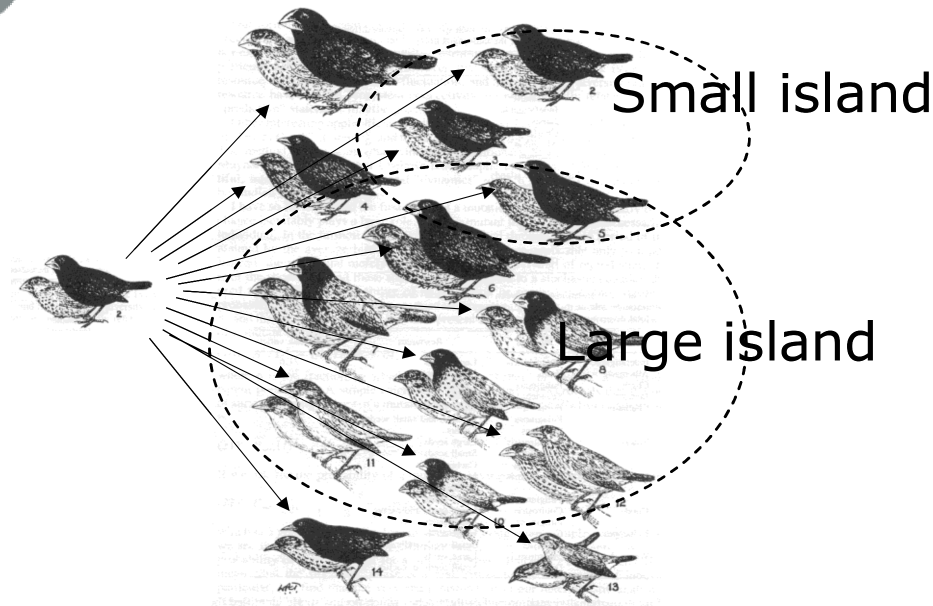
Complex Systems

Cranfield UNIVERSITY

- Multiple heterogeneous elements, dynamical, self-organizing, innovative/creative, sustaining the current system and creating the future
- Context matters, initial conditions, histories, boundaries are permeable
- Agents are coupled within and without the system; but effect of local interactions on system's behaviour is unknown; feedback, non-linearity, multi-equilibria, multi-scale

Examples

- Termites
- Finches
- Typhoons
- Production/distribution systems
- Firms
- Supply Networks
- Financial Markets
- Etc…..



Darwin's Finches

What is a model?

Cranfield UNIVERSITY

- An analytical technique
- Two broad strategies:
  - Collect data, analyse and create a ‘rich’ model to describe the system
  - Use existing theory to create a computation model to explain system
- Can’t experiment in a complex system; there is no ‘control’ system to compare against

Models – to simplify or to absorb?

Cranfield UNIVERSITY

Strategies - *Reduction* and *absorption* for handling complexity (Boisot and Child 1999) - objectivists are complexity-reducers while interpretivists are complexity-absorbers.

The former **favour models** while the latter explore meanings and are more likely to advocate metaphoric treatments, although the distinction is not as sharp as one might think.

Not Science
Heuristics
Intuition
Literature
Descriptions....

Ralph Stacey – complex responsive processes

Peter Checkland – soft systems methodology

No assumptions or knowledge?

Computational Model features

- Scale Models
  - Reduction in size or number of features
- Ideal-Type
  - Some characteristics exaggerated – ‘perfect information’
- Analogical
  - Representation by more familiar objects – billiard balls for atoms

Computational Models - ideal types

Cranfield UNIVERSITY

Purpose	Constraints	Types of Model	Features
Competitive Strategy	Boundary & classification	Learning and evolutionary ABM	Evolutionary, adaptive change
Contingency	& reduced heterogeneity	Self-organizing, probabilistic, non-linear, dynamic multi-agent models	Fixed elements; ignores the past; represents current interactions; tests resilience
Operations	& average types, smooth behaviours	Deterministic, system dynamics; micro-simulation	Identify limits to performance given a fixed environment and limited diversity
Stationarity; equilibrium	& probabilistic macro stability	Simultaneous equations; power laws, SEM & equations	Prediction for structurally stable systems; ignores dynamics

Considerations for computational models

- Programming form
- Environment
- Order in which activity takes place
- Building in error-making/randomness
- Measuring outputs

Programming methods for computational model

Cranfield UNIVERSITY

- Object-oriented programs
  - Java, C++
  - Classes – instantiated as objects/agents, each with own memory (attributes values), methods to send messages and to process data according to policies.
- Production Rule Systems
  - Assign rules/behaviours to agents, working memory, rule interpreter, an input and output process
- Artificial Neural Networks
  - Layers of stacked units, all units in each layer connected below and above; ANN can be trained to recognize patterns and then decode new inputs

Gilbert, 2008

Environment

- Objects in the environment can be coded as ‘passive’ agents, e.g.
  - roads which transport goods (and have attributes such as distance, and randomly created properties, such as hold-ups),
  - warehouses for storing goods,
  - networks for transferring information,

Order and Randomness

- Digital processing/execution means choosing an order for agents to act
  - Sequential asynchronous = in the same order at every time step;
  - Randomize the order between time steps (random asynchronous);
  - Any convenient order (simulated synchronous)
- Event-driven – not all agents act at each time step
- Build in random errors in processing to emulate noise
- Random selection of initial conditions and links

Outputs

- What measure(s) reflect the system's activities?
  - Profit or longevity of the agent?
  - Number and size of clusters/sub-systems?
  - Representation of the dynamics
- How to represent the outputs of the model?
  - Visualization – 2D, 3D, more?
  - Graph as t increases?
- How to calibrate the time of the model to real-time?

Evolutionary Models

Purpose	Constraints	Types of Model	Features
Competitive Strategy	Boundary & Classification	Learning and evolutionary ABM	Evolutionary, adaptive change

Evolutionary Models – not structurally stable

- If the system is structurally stable then prediction, either dynamic or static, is possible even if probabilistic.
- But structural stability means no real innovations – and probable extinction in a changing environment
- Innovation occurs via learning, experimentation, …

What is learning?

Cranfield UNIVERSITY

- Market/sector level, inter-firm learning, e.g. innovation networks or industrial districts in which firms compete (sell the same product) and collaborate (e.g. suppliers, logistics, finance); learning about others
- Individual level, experiential learning; but beware the context
- Evolutionary learning from the failure of others and supersession by new, more competent firms
- Social learning from others by imitation or teaching; importance of networks or access to new knowledge

Gilbert et al, 2006

Complexity of Markets: Creative Destruction

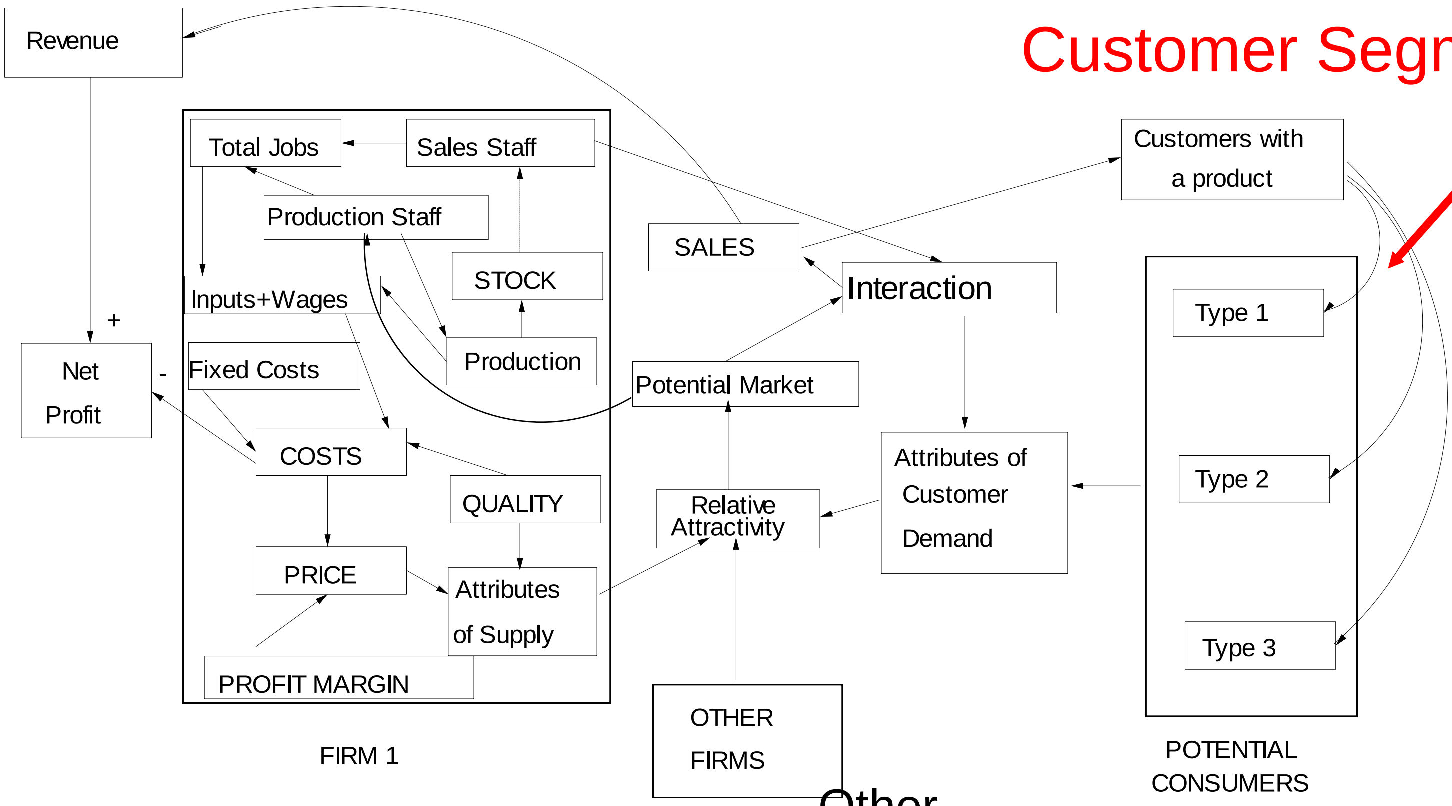
- Schumpeter in 1938 said “the problem is not how capitalism administers existing structures but how it creates and destroys them”
- Average life of S&P firms has fallen from 65 years (1920-1930) to 12 years (2000)
- In the last 55 years only 17 firms survived the period, but all but one had a return on investment less than the overall market gain
- Paul Ormerod modelled the life expectancy of firms under different hypotheses about their capacity to learn: He finds that the model that fits best is the one corresponding to random extinction and very little learning. (Why most things fail, 2007)
- The real task is to transform the company as fast as the market is evolving! (Foster and Kaplan, 2001)

A Multi-Agent Economic Market Model:

Cranfield UNIVERSITY

Agent n

Customer Segments

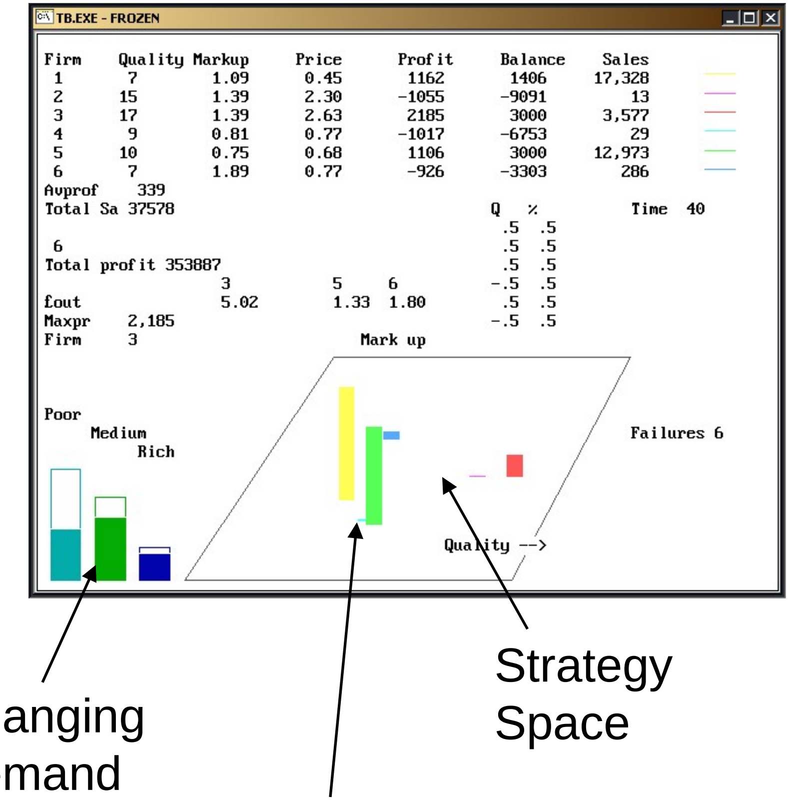


Other Agents

Strategy on Profit Margin,
Quality, R&D, Design….

Simulating Market Evolution:

- Multi-agent models can demonstrate how the exploration of strategy space leads to an “ecology” of agents.
- Selection operates through consumer choices, but the agents may change over time, and their learning rules co-evolve



Changing Demand

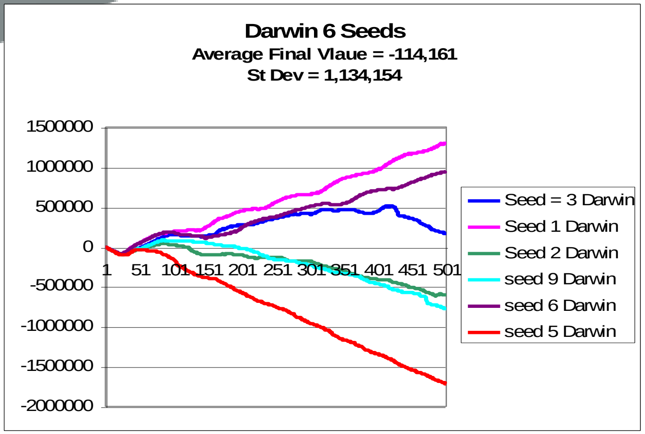
Strategy Space

6 interacting firms/agents Evolving supply

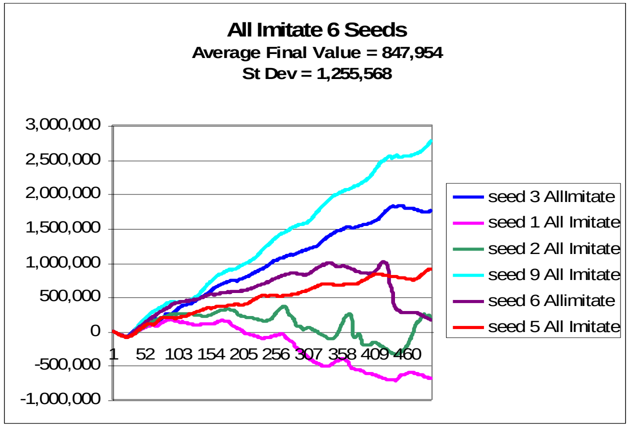
CONTEXT:
Multi-agent market

model to investigate simple product pricing and quality strategy

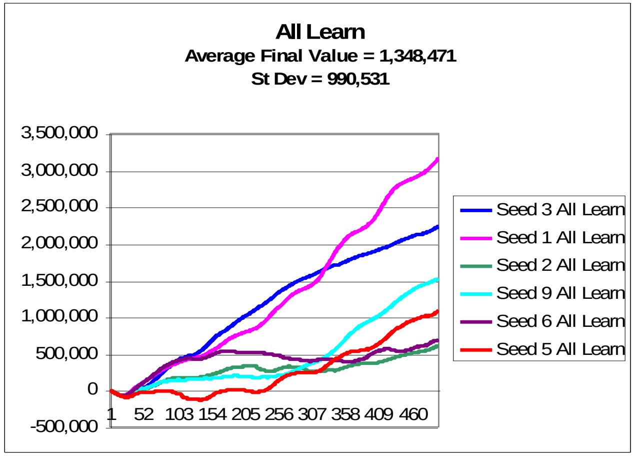
Darwinian



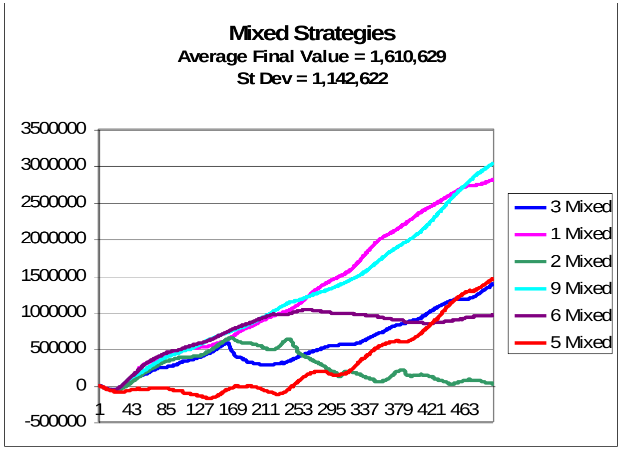
Imitate the Winner



All Learn by Experiment



Diverse Strategies

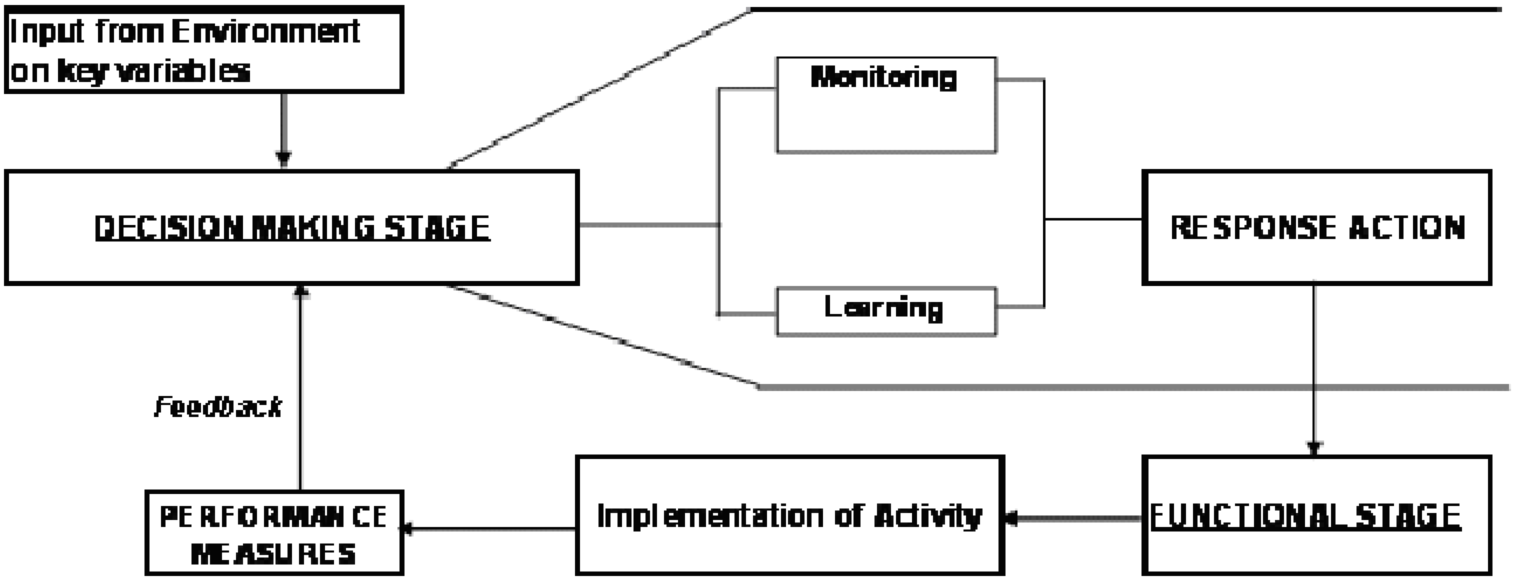


Contingency Model

Cranfield UNIVERSITY

Purpose	Constraints	Types of Model	Features
Contingency	Boundary & classification & reduced heterogeneity	Self-organizing, probabilistic, non-linear, dynamic multi-agent models	Fixed elements; ignores the past; represents current interactions; tests resilience

Paper Factory - Generic Agent Structure

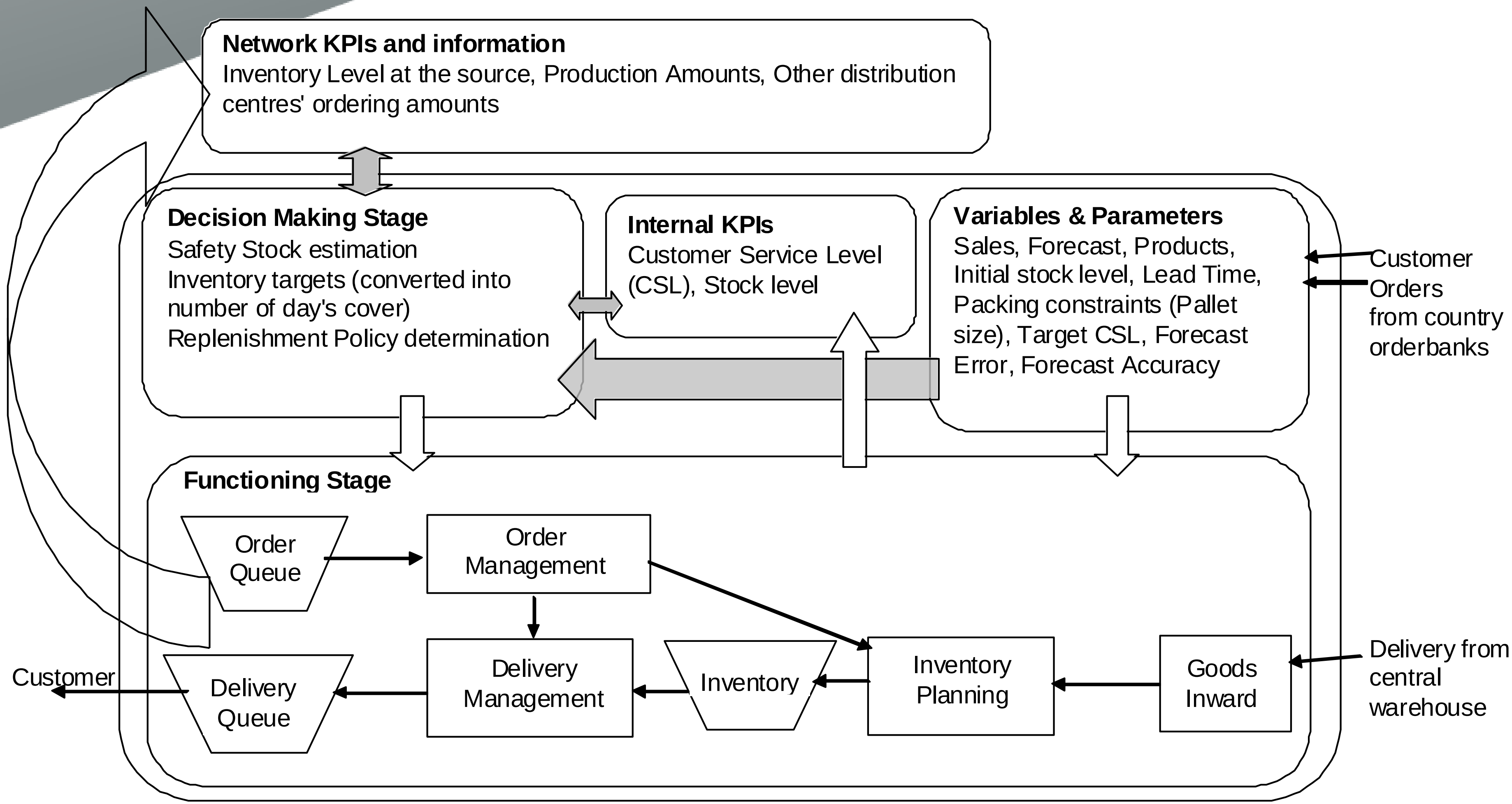


A combination of three different types used

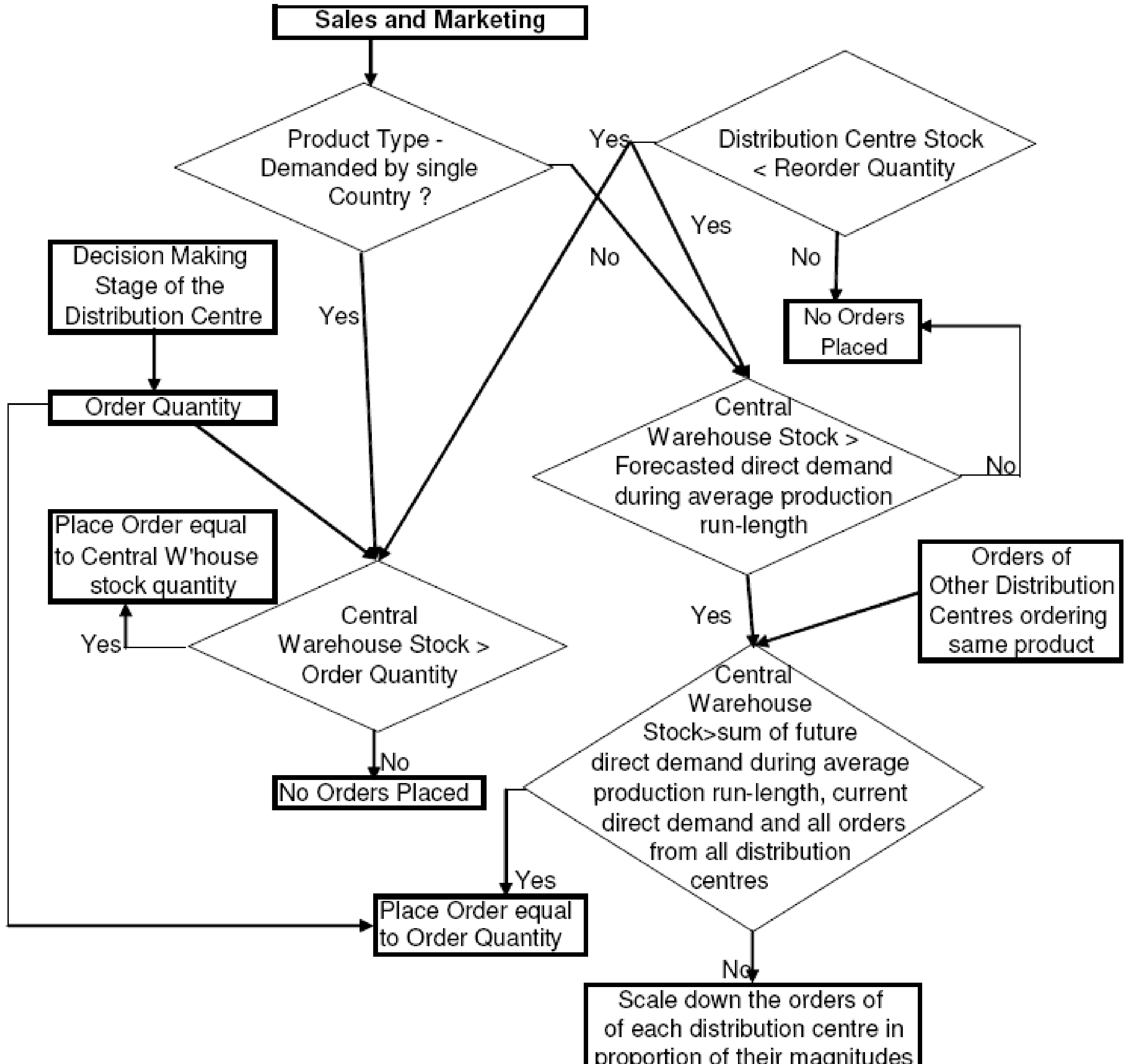
- Agents respond to any change in the environment
- Agents act on perceived view of future environment
- Agents learn from their actions in real-time

Internal Architecture of Distribution Centre (DC) Agent

Cranfield UNIVERSITY



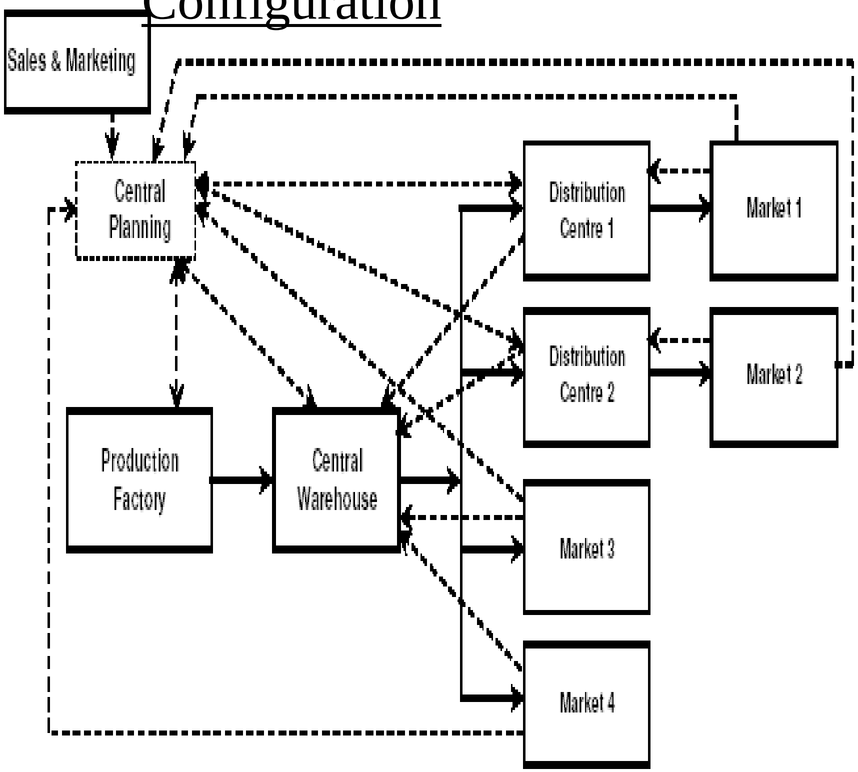
An Instance of decision making schema of the agent



Findings - Baseline Model under uncertain demand

Cranfield UNIVERSITY

Configuration



Agent Decision Rules

- The central planning optimises the cost of operation by minimising production stoppage time, inventory holding cost at central warehouse and DC's
- Factory produces planned amounts but optimises changeover time
- The central warehouse sends materials randomly to DC's in case of scarcity

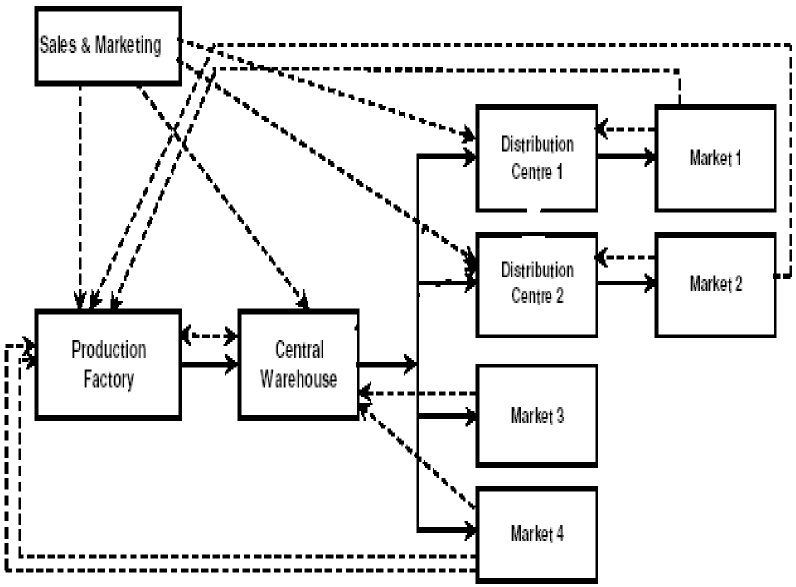
Results over one year

- Average network inventory 144519
- Average network service level 95.7%
- Average stock outs across network 148
- Average total number of changeovers 103
- Average response time to disaster 5.7 days

Findings - Model with distributed decision making

Cranfield UNIVERSITY

Configuration



Agent Decision Rules

- The factory optimally decides production plan minimising stoppage time, central warehouse inventory; low volume products are produced less often
- The factory uses fixed minimum production time for each product
- Each DC optimises ordering decision based on own inventory
- The central warehouse sends materials randomly to DC's in case of scarcity

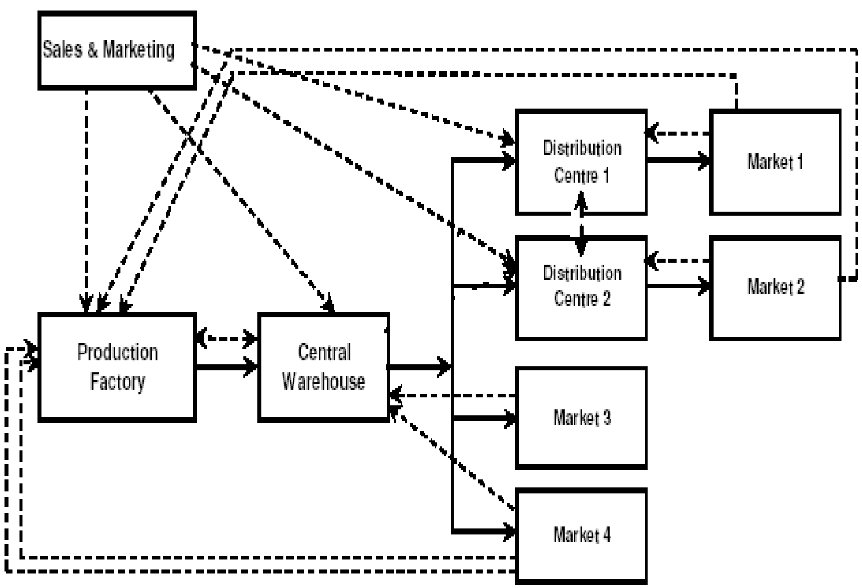
- Average network inventory 146872
- Average network service level 96.4%
- Average stock outs across network 148
- Average total number of changeovers 102
- Average response time to disaster 5.6 days

Outputs over 1 year

Findings - Model with distributed decision making & collaborative DCs

Cranfield UNIVERSITY

Configuration



- Average network inventory 123560
- Average network service level 98.5%
- Average stock outs across network 29
- Average total number of changeovers 79
- Average response time to disaster 6.1 days

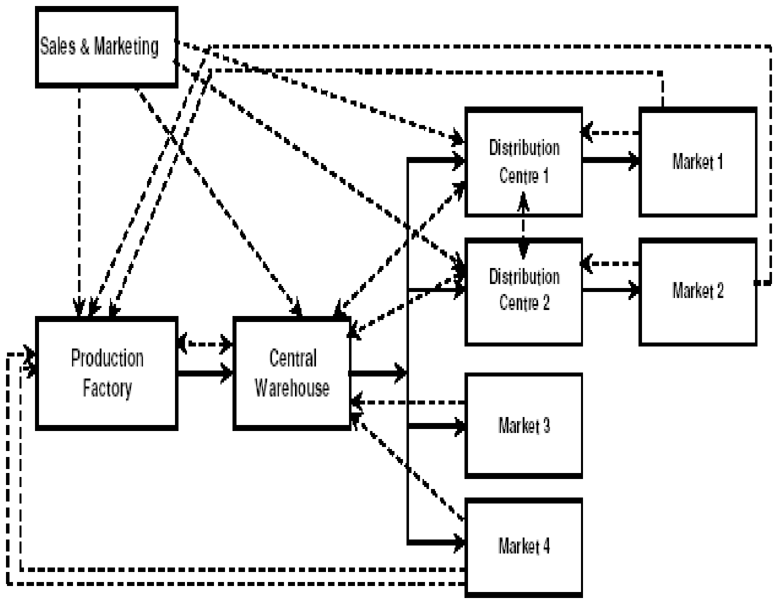
Agent Decision Rules

- The factory optimally decides production plan minimising stoppage time, central warehouse inventory; low volume products are produced less often
- The factory uses fixed minimum production time for each product
- Each DC optimises ordering decision based on own inventory
- Each DC now collaborates with each other in case of scarcity of materials at central warehouse

Results over one year

Findings - Model with distributed decision making, full information-sharing

Configuration



Results over one year

- Average network inventory 147017
- Average network service level 99.8%
- Average stock outs across network 13
- Average total number of changeovers 79
- Average response time to disaster 3.4 days

Agent Decision Rules

- The factory optimally decides production plan minimising stoppage time, network inventory; low volume products are produced less often
- The factory uses full network inventory information for scheduling production
- The factory learns minimum production time for each product
- Each DC optimises ordering decision based on own inventory and considering risks of stockouts
- The central warehouse allocates materials in case of scarcity based on a fair share rule
- The central warehouse pushes direct demand materials as soon as they are produced

Different Scenarios & Capabilities

Cranfield UNIVERSITY

Configuration	Information Sharing	Efficiency	Flexibility	Normal Operations					Unexpected	
				Average Inventory	Average Service	Average S.O.	Average Setups	Average Resp.	Factory Breakdown Service	Delay Service
Centrally optimised production plan	Factory decides schedule based on Central Warehouse stock information No information sharing across RDCs	RDCs order materials optimising own inventory	No consideration in factory or RDCs	144519	95.70%	148	103	6 days	95.95%	94.50%
Decentralised decision making	Factory uses Central Warehouse stock information to guide production No information sharing across RDCs	RDCs order materials optimising own inventory	No consideration in factory or RDCs	146872	96.40%	149	102	5.6 days		
Decentralised decision making	Factory uses Central Warehouse stock information to guide production Each RDC shares information on network stock, demand, forecasts	RDCs order materials collaboratively in case of scarcity, otherwise optimise own inventory	No consideration in factory or RDCs	123560	98.50%	29	79	6 days	98.93%	98.10%
Decentralised decision making	Factory uses whole network stock information to make decisions on production planning Central warehouse uses information to send materials to RDCs	RDCs order materials using adjustable safety stock to optimise stock and safety	RDCs can change target stock flexibly; factory changes run-length based on production frequency	147017	99.80%	13	79	3.4 days	99.70%	99.60%

Paper Factory Summary

- Analytical method to understand the key issues essential for improving operational resilience in a complex production distribution system
- Model highlights the importance of:

  - knowing earlier

  - managing-by-wire

  - designing a supply network as a complex system

  - flexibility in production and dispatching capabilities from the customer request back

  - balancing push and pull type replenishment

  - balancing safety and efficiency

Modelling

Cranfield UNIVERSITY

Purpose	Constraints	Types of Model	Features
Competitive Strategy	Boundary & classification	Learning and evolutionary ABM	Evolutionary, adaptive change
Contingency	& reduced heterogeneity	Self-organizing, probabilistic, non-linear, dynamic multi-agent models	Fixed elements; ignores the past; represents current interactions; tests resilience
Operations	& average types, smooth behaviours	Deterministic, system dynamics; micro-simulation	Identify limits to performance given a fixed environment and limited diversity
Stationarity; equilibrium	& probabilistic macro stability	Simultaneous equations; power laws, SEM & equations	Prediction for structurally stable systems; ignores dynamics

Supply Network Principles for Retail

3rd Nov 2009

Dr Liz Varga
liz.varga@cranfield.ac.uk

Questions?