SIMulators in business: Testing the impossible, discovering the probable

By Chris Langdon 2019, update Q2 2020

Table of Contents

Simulators for products and services … and entire ecosystems 1
What is computer simulation? 2
Why use simulations? 2
Trusted simulators built from science 4
Acknowledgements 5
References 5

Simulators for products and services … and entire ecosystems

We are known for solving real business problems and optimizing performance using advanced analytics and computational simulation or decision support systems (DSS) powered by artificial intelligence. Focal domains have been the automotive and mobility industries. They share similarities and exhibit key differences: both involve Sales & Marketing, Development, and Finance. They optimize different outcomes, however. Automotive concerns a manufacturing business, mobility is a service. In the automotive industry the product is what matters; with a service retention is key (see our story on “Smart Mobility & Auto”). Therefore, auto is focused on building the perfect car to win the customer; a mobility service is focused on fighting churn to hold on to the customer. We have built dashboards and simulators for both objectives: how to win customers and how to keep them. Examples include:

- The “calculator” for optimizing vehicle interiors and UX is focused on creating the perfect vehicle interior to win the customer, see “Auto Interior & UX.”
- The “calculator” for mobility-as-a-service is designed to provide decision support for keeping customers; see “Mobility-as-a-Service.”
- We also developed simulators for optimizing supply chain and distribution channel resilience: How could the next recession affect the Nissan business ecosystem in the U.S. market?

What is computer simulation?

According to Encyclopedia Britannica, “a simulation uses a mathematical description, or model, of a real system in the form of a computer program. This model is composed of equations that duplicate the functional relationships within the real system.” In the sciences, simulations generate computational explanations of real-world phenomena and complement more traditional scientific laws (e.g., Newtonian physics) and axiomatic (e.g., utility theory in economics) explanations (see Kimbrough, Research Note - Computational Modeling and Explanation, SIGABIS Exchanges 1(1), pages 3-4) (link). Computational models are typically inspired by natural phenomena, mimicking biological, evolutionary processes, such as with genetic algorithms and neural networks (Holland 1995). In business, simulations allow for imitation – and also learning from imitation, creating not just a digital twin of a product, a process, a company, a market, and ecosystem – but an “artificial” one that exhibits adaptive behavior.

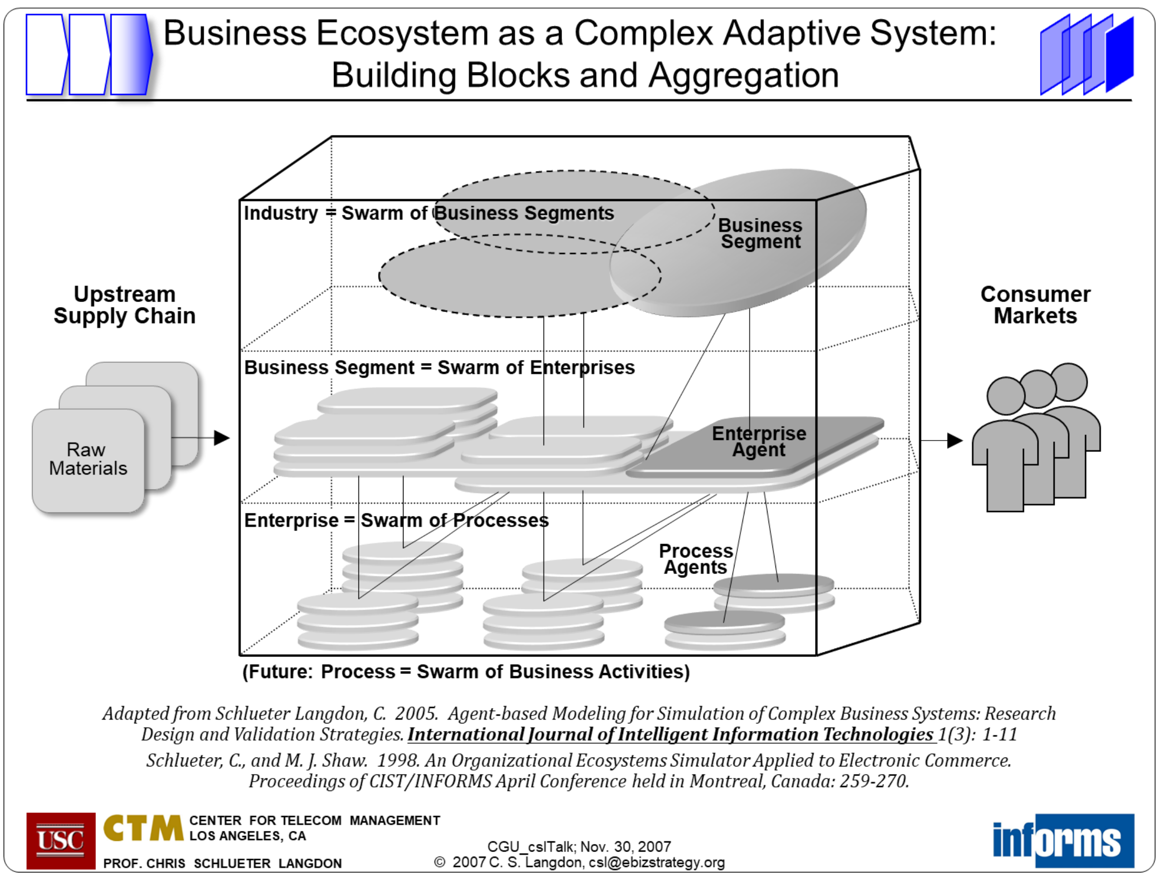

Figure 1: A complex adaptive system implemented as a multi-agent system

Why use simulations?

Most importantly, simulations allow for experiments that would otherwise be either impossible or severely limited:

- How to test the future without endangering humans, your employees, customers, focus groups … the public?

- How to predict the future using statistics - which is an extrapolation of the past - if the future is explicitly a structural break from the past, such as a recession, new regulation, or the launch of a revolutionary product, such as the Apple iPhone?

Specific advantages include:

- Multi-step games instead of single-shot analysis (playing through a series of attacks and countermeasures).
- Multi-party wargaming (recognizing more than one competitor).
- Observations of emergent behavior and recognition of system-level feedback (product launch, buyer behavior shifts, new markets, ecosystem formation).

Feedback from the whole system on interactions of its parts inevitably creates non-linear terms that cannot be solved analytically (see Holland 1995). Figure 1 illustrates a system in which performance emerges from the interactions of lower level agents, which in turn, are dependent on system-level feedback. An example of this is profit - defined as revenue minus cost. The cost part is controlled by each firm; the revenue element is dependent on the whole system (top level) as market price is the cumulative result of each seller's offer and each buyer's bid (lower level).

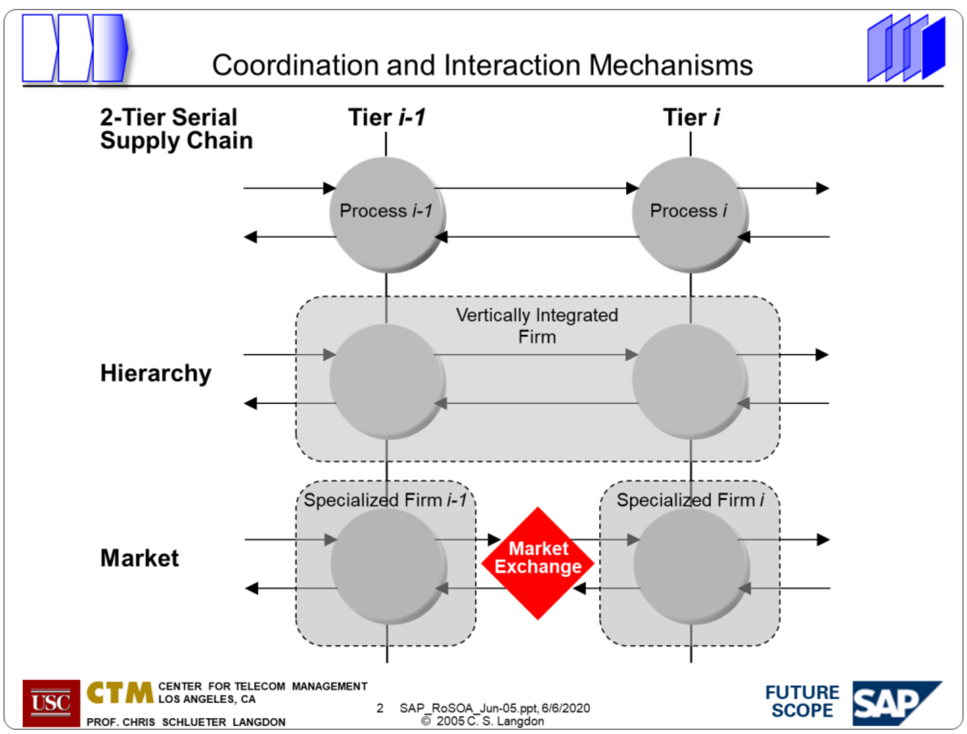

Figure 2: Vertical integration versus coordination via markets

Trusted simulators built from science

Our simulators' foundation is built on a line of work that has evolved from Simon (simulation and science of the artificial, 1978 Nobel Prize in Economic Sciences, link), Smith (laboratory empirical experiments or "wind tunnel" in economics, 2002 Nobel Prize in Economic Sciences, link), Holland and Goldberg (genetic algorithms and complex adaptive systems), Whinston and Shaw (agent-based modeling and learning) to allow for computational laboratory experiments in business scenarios that exhibit complex interactions and recognize many different types of actors, such as buyers and sellers, suppliers and consumers, as well as configurations, such as supply chains and channel systems. Experiments can recognize different settings for:

- Competitive strategy (price and/or quantity, referred to as Bertrand or Cournot competition respectively)
- Industry structure (many/few/monopoly seller, many/few/monopoly buyer)
- Upstream structure in the value chain: multi-tier supply chains (tier 1, tier 2 ... tier n)
- Downstream structure: multi-tier channel systems (direct sales, retail, wholesale) and multi-channel layouts
- Macroeconomic or overall "weather" conditions (boom, stagnation, recession)
- Up- and downstream coordination (contracts or competition). Figure 2 visualizes how coordination between two successive agents (people, processes, firms, industries …) can be organized by contract or vertical integration, market competition (price, output) or any combination of the two.

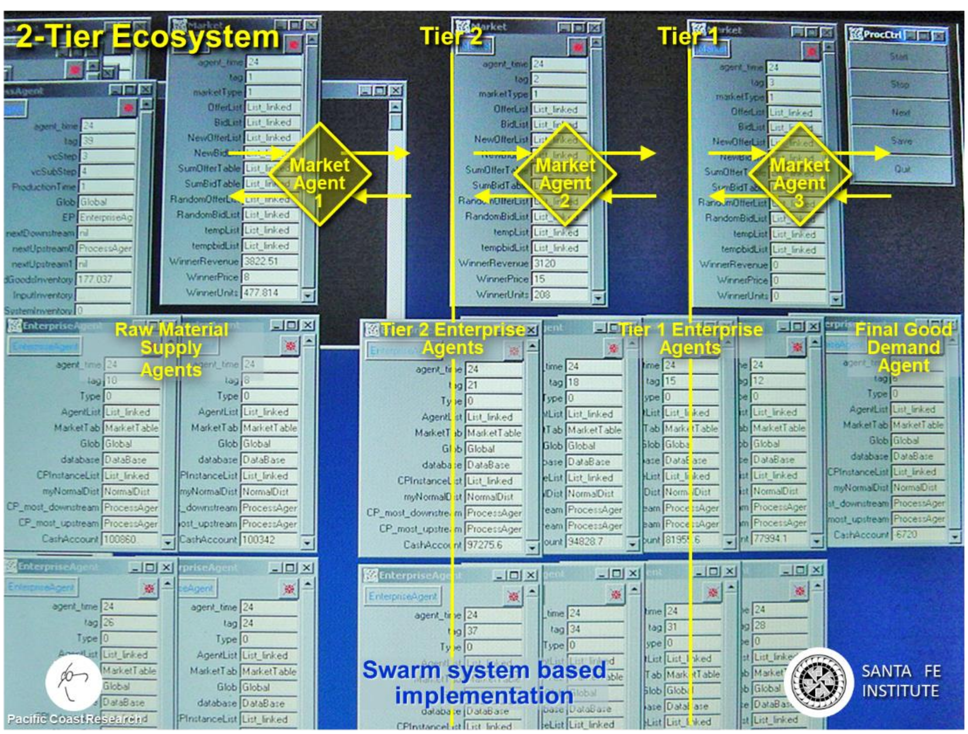

Figure 3: Screenshot of a living artificial business ecosystem

All of the above is enabled by multi-agent modeling (Sikora & Shaw 1998), agent learning (Sikora & Shaw 1996), and implemented using various software kits, particularly Sante Fe Institute's Swarm, an object-oriented platform for the simulation of complex adaptive systems (overview, link; resources, link).

Figure 3 is a screenshot of a living Swarm-based simulator for an artificial two-tier business ecosystem with three markets connecting the tiers and probe windows or monitors for each "living" agent, the market agents and the enterprise agents and their lower-level process agents. The probes are a simulator feature which allow for constant monitoring of individual agent "health" and manually interfering with agent behavior by changing values of key parameters, for example. In order to create artificial business ecosystems - as opposed to biological ones, for example - the Swarm platform has been expanded with a set of libraries to enable models grounded in economic theory (ORECOS, Organizational Ecosystem Simulator; Schlueter Langdon & Sikora 2006, Schlueter Langdon 2005, Schlueter Langdon et al. 2000).

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SIGABIS, Special Interest Group on Agent-based Information Systems for the Association of Information Systems (AIS). Co-founded in 2001 by Schlueter Langdon and Sikora with board members Shaw (U of Illinois), O'Leary (USC), Kimbrough (Wharton School) and the honorary board member Holland (U of Michigan, Santa Fe Institute, World Economic Forum)

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