

TUTORIAL ON BUSINESS AND MARKET MODELING TO AID STRATEGIC DECISION MAKING: SYSTEM DYNAMICS IN PERSPECTIVE AND SELECTING APPROPRIATE ANALYSIS APPROACHES

Donna D. Mayo

Decision Sciences Practice
PA Consulting Group
One Memorial Drive, 16th Floor
Cambridge, MA 02142, U.S.A.

Knud Erik Wichmann

Decision Sciences Practice
PA Consulting Group
Tuborg Boulevard 5
2900 Hellerup, DENMARK

ABSTRACT

System dynamics models have been used to address strategic questions in many hundreds of companies and government agencies around the world over the past 40 years, including a broad range of organizations in the transport sector. However, this technique remains less well known than other approaches among potential client organizations and within the simulation community. This paper provides a pithy tutorial on the system dynamics method and the modeling process, uses transport sector case examples to illustrate how such models have been valuable in practice, and compares key characteristics of system dynamics to discrete event simulation. We close with some guidance on factors to consider when selecting an analysis approach that is appropriate to the problem under study.

1 INTRODUCTION

Following its invention at Massachusetts Institute of Technology in the early 1960s, the system dynamics method has been used to address some of the most challenging strategy questions facing business and government over the past 40 years. There exists an impressive record of successful applications of this modeling method. The 2001 winners of the Franz Edelman Prize for excellence in management science included a team from General Motors who developed a system dynamics model to develop a successful strategy for launch of the Onstar system (Huber et al. 2002). Yet system dynamics modeling continues to be less well known than other techniques, within both the client community and the broader simulation community.

While we cannot within the constraints of this short paper provide a full explanation of the system dynamics method, we will try to share what we believe to be the most critical characteristics that underlie the technique. In Section 2 we provide an overview of the fundamentals of the system dynamics approach, followed by a walk through

the steps in the typical process of developing and using a model in Section 3. In Section 4, we use several case examples of system dynamics modeling in the transport sector to illustrate the range of problems that are effectively addressed by this methodology. We summarize some of the key differences between system dynamics and discrete event simulation in Section 5. We conclude in Section 6 by offering some guidance on factors to consider when selecting an analysis approach that is “fit for purpose” given the problem under study.

2 WHAT ARE THE KEY CHARACTERISTICS OF SYSTEM DYNAMICS?

System dynamics modeling provides a means of representing the key performance drivers, and their interdependencies and interactions, within dynamically complex businesses and environments. There are several important elements of the system dynamics method that enable this to be achieved, including:

1. Cause-effect relationships
2. Representation of feedback loops
3. Time-delayed responses
4. Non-linear responses
5. Representation of decision rules

Each of these is described below.

2.1.1 Cause-Effect Relationships

System dynamics starts by identifying and representing the underlying factors that drive behavior. These reasons are explicitly represented as *cause-effect relationships*. For example, as seen in Figure 1, price affects sales. Of course, there are other factors that also affect sales, and price is itself driven by other factors. It is the description of these many driving forces and their interrelationships that forms a system dynamics model.

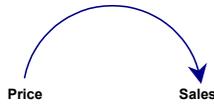


Figure 1: Cause and Effect Relationship Between Price and Sales

2.1.2 Feedback Loops

When traced back through causal chains, many of these cause-effect relationships feed back upon themselves, forming *closed feedback loops*. For example, a low product price may stimulate sales, allowing a company to achieve economies of scale that reduce cost, allowing an even lower price, and so on, as illustrated in Figure 2.

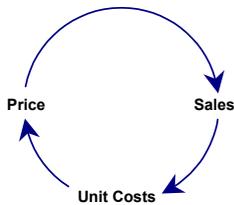


Figure 2: Feed Back Loop Effecting Price, Sales and Unit Costs

This is an example of a positive or self-reinforcing feedback loop, in this instance also known as a “virtuous circle.” Self-reinforcing loops may also work in the other direction and become “vicious circles,” for example, low sales may increase the unit cost of production, forcing higher prices, further *hurting* sales.

The most important factors in a complex environment are affected by more than one element, and it is the cause-effect interrelationships among many factors that make the world both complicated and interesting. To extend the example a little further, note that sales can be affected not just by price, but also by supporting service quality. However, if sales grow to the point where they stretch the capacity for excellent service, quality may suffer, hurting subsequent sales. This dynamic can be represented as follows in Figure 3.

In this case, the introduction of service quality introduces a *negative or self-correcting feedback loop*, also

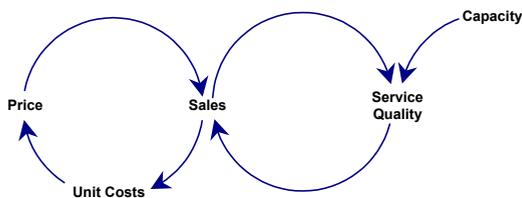


Figure 3: Two Feedback Loops Acting Simultaneously

called a balancing loop. This second loop illustrates why price cuts to stimulate volume growth can be futile unless there are parallel increases in service capacity. These two loops above could be extended to incorporate many other factors that determine the behavior of the system; for example, higher sales increase delivery delays, which in turn feedback to constrain subsequent sales growth.

In addition to these networks of cause-effect relationships, the system dynamics methodology explicitly treats other important elements of behavior in the real world, as described in Sections 2.1.3 and 2.1.4.

2.1.3 Time-Delayed Responses

Many of the cause-effect relationships that drive business performance exhibit delayed responses. For example, as illustrated in Figure 4, it may take months for marketing effort to have an effect on revenue.

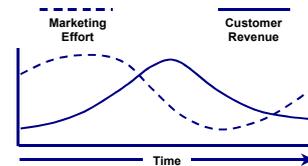


Figure 4: The Delayed Response of Customer Revenue to Marketing Effort

Failure to take such delays into account may lead to the wrong decisions - for example, changing marketing strategies at just the wrong time, because the effects are not immediately apparent.

2.1.4 Non-Linear Responses

Aside from such delays, many real cause-effect relationships are characterized by non-linear responses, in which the resulting effect is not in constant proportion to the cause. To develop further the marketing example cited above, marketing expenditures below a certain level might have negligible effect; and additional marketing *above* a certain level can reach saturation or diminishing returns. This kind of relationship can be illustrated by an S-shaped curve shown in Figure 5.

Other examples abound: the effect of market share on competitive response, the effect of price differentials on the importance of quality in consumer decision making, and the degree of staff skill dilution from varying staff growth rates. Taking such non-linearities into account is critical to making sound decisions.



Figure 5: The S Shaped Curve Describing the Relationship between Customer Revenue and Marketing

2.1.5 Representing Decision Rules

What happens within and outside a business or other environment is ultimately driven by the many decisions that are made by the actors within the system, including management, government, the competition, customers, suppliers, regulators, and so on. These decisions are based on information, and affect decisions made by other parties as illustrated in Figure 6. System dynamics can explicitly represent the underlying incentives and information that drive the ongoing decisions that cause system behavior to unfold as it does.



Figure 6: The Information Available Within the Organization Affects the Decisions Made

2.1.6 System Dynamics Equation Building Blocks

Equations are built up using the fundamental building blocks of levels and rates. (Refer to Sterman 2000 for an excellent and more comprehensive introduction to the technical aspects of system dynamics modeling.) All systems consist of accumulations of ‘things’ and actions or activities. Levels are used to represent anything that accumulates; rates are used to represent any activity or action. A useful metaphor may be to think about a level as a bathtub and a rate as the pipe that fills or drains the tub. Tubs hold a given amount of water and the pipe either fills or drains the tubs at a specific rate, or volume of water per unit of time. In calculus terms, the levels are the integrations, and the rates are the derivatives.

So, levels represent anything, tangible or intangible, that accumulates. Some familiar accumulations include balance sheet items (e.g., cash or inventory), order backlogs, and headcount. However, levels also can represent

such non-physical concepts as “customer knowledge” and “relationship with investors.” Levels are depicted in the system dynamics language as rectangles.

Rates represent the processes or activities that adjust levels. Examples include income statement items or such time-dependent processes as hiring (adjusts headcount), ordering (adjusts backlog), and shipping (adjusts inventory). A rate is depicted as a rate regulator, which is depicted as a valve connected to a circle, attached to a ‘pipe’ that originates and terminates at either a level or a ‘cloud.’ It is important to note that rates are *directional*. An arrowhead at the end of the pipe indicates the direction of the rate.

‘Clouds’ represent the boundaries of a model and are considered to be infinite sources of, or sinks for, the material being transported by a rate.

A simple level-and-rate structure is depicted below in Figure 7.

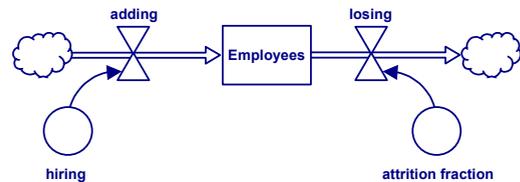


Figure 7: Levels and Rates Are the Fundamental Components of Model Structure

3 THE SYSTEM DYNAMICS MODELING PROCESS

System dynamics models frequently include the representation of hundreds of interconnected and often non-linear cause-effect relationships, often involving significant time lags, and the many feedback loops formed as chains of relationships converge. Figure 8 lays out the basic steps in the modeling process, and the following sub-sections describe the key aspects of the process. It is normal to revisit steps in this process during the course of model refinement or expansion, or when receiving enhanced information.

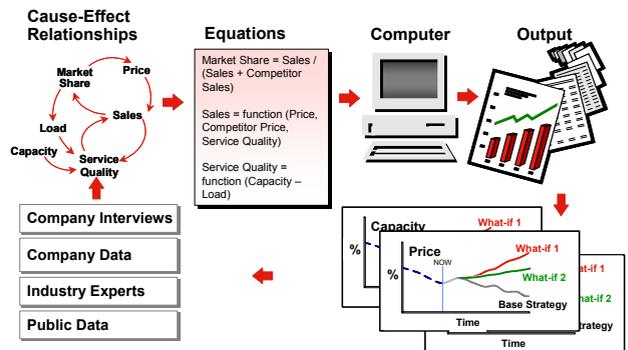


Figure 8: The Basic Steps In The Modeling Process

3.1.1 Document the Key Cause-Effect Relationships

In creating a system dynamics model, the first step involves identifying and documenting the set of cause-effect relationships that characterize the workings of the system (e.g., a business, an industry, a surface transport environment) under study. To do this, the modeling team considers a broad range of information, including interviews with those who have working knowledge of key system components, company data, published research and data about other aspects of the system (e.g. competitor performance), and the like. The first output is thus a qualitative framework that illustrates the key drivers of performance and how they are interlinked. The framework serves as the “blue print” for the initial quantitative system dynamics model.

Often referred to as “systems thinking”, such frameworks can be quite valuable in themselves. It is typical for an initial analysis to be performed using the framework to understand the implications of proposed changes to strategy. In particular, such a qualitative analysis can help to identify areas of opportunity, risk, and uncertainty and to understand how contemplated actions will likely impact other parts of the system.

3.1.2 Build and Validate the Quantitative System Dynamics Model

The next step expands the initial qualitative framework into a series of interlinked mathematical equations that specify how the elements are related quantitatively. The equations are developed using the basic components of levels and rates as previously described in Section 2.1.6.

There are several system dynamics modeling packages that provide a visual vehicle for building the equation structure required, including iThink, Powersim, Vensim, and Jitia. PA Consulting has developed the Jitia simulation software to serve the simultaneous aims of permitting the construction of large, complex models and enabling ease of explanation and use with clients. Figure 9 shows the hierarchical “folder structure” of a typical large model developed in Jitia and “drills down” to show the underlying equation structure for one segment within the model. (See Eubanks and Yeager 2001 for additional description of Jitia.)

Validation is an integral part of the model building process. There are five principle steps. First, the cause-effect logic and individual equations comprising the model are assessed for reasonableness. Second, the strength and timing of the cause-effect relationships are checked for consistency: (i) with one another; (ii) with the experience and judgment of people knowledgeable about the system; and (iii) with similar relationships encountered in modeling comparable systems. Third, the model is required to re-create faithfully the documented performance over the

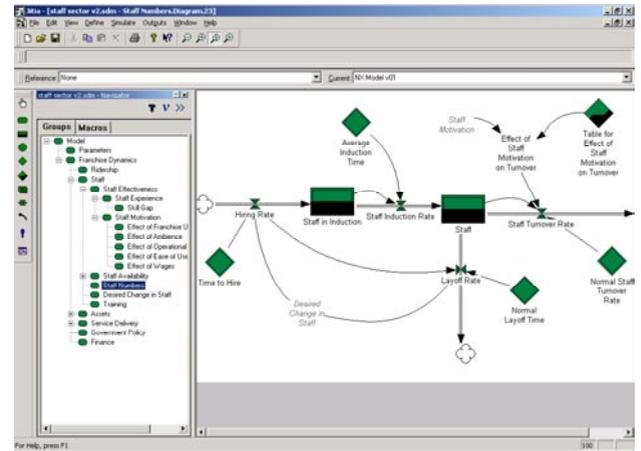


Figure 9: Equations in a Typical Large System Dynamics Model

course of time, without making any direct computational use of the historical data describing that performance. Fourth, the re-created simulation is carefully scrutinized for its fidelity to all available knowledge (both measurable and qualitative/judgmental) concerning the factors that determined actual historical performance. Fifth, the model equations and parameters are tested for reasonable behavior under different and extreme conditions.

3.1.3 Ask and Answer “What If...?” Questions

The last step involves putting the model to use. The validated model is now ready to perform its main and most valuable function – answering a broad range of “what if” questions. “What if” testing allows the organization to experiment in advance – before committing to action – with the full, long-term consequences of potential proposals, actions or changed conditions. Proposals can be considered both individually and in combination, allowing identification of those actions that are synergistic (i.e., the combination delivers a higher level of benefits than analysis of each one individually would suggest) and those that conflict with each other and wipe out the intended benefits. In practice such models help organizations to:

- Find actions that produce the largest desired benefits
- Fine tune the timing and sequencing of strategy implementation
- Spot and mitigate undesirable consequences that arise under a potential set of actions.

Additionally, the system dynamics modeling toolset brings with it powerful automated analysis capability that can enhance the ability of organizations to explore a rich selection of policy options, via for example:

- Sensitivity testing – “Which actions make the most difference to the desired outcomes?”

- Monte Carlo analysis – “Given a potential range of action effectiveness, what is the expected value of benefits delivered, and over what expected time frame will they be delivered?”
- Optimization – “Given a goal of obtaining a particular set of benefits within a particular time frame, what is the optimal mix of actions to achieve this?”

The major system dynamics modeling packages also support running simulations through programming interfaces, so that more complex analyses (e.g. hybrids of the above) can be written in a high-level programming language of the modeler’s choice.

System dynamics modeling makes it possible to integrate all of the key environmental and behavioral elements and their interrelationships into a single consistent, explicit, and flexible strategic level analysis system. The case examples in the next section demonstrate the types of value that can result from use of such models.

4 TRANSPORT SECTOR CASE EXAMPLES USING SYSTEM DYNAMICS

In this section, we provide several brief case examples based on PA Consulting Group’s experience developing and using complex, numerically validated system dynamics models with organizations in the transport sector. Sharing real stories is frequently the best way to convey how analytical tools are most valuably used. These examples span a broad and quite different range of strategic issues, including generating reliable market forecasts in the cyclical aviation sector, helping a metro subway system through a difficult restructuring, providing a tool to assess the consequences of carrier and government policy decisions on U.S. shipping, and diagnosing and explaining the cost and schedule performance of a major rail infrastructure development project to support a contract dispute. Where available, we refer to other papers that can provide the interested reader with more information on specific cases.

4.1 Airbus Industrie: Producing Reliable Forecasts of New Jet Aircraft Orders

Airbus sought a better way to forecast aircraft orders over 5 to 10 year periods in order to make critical decisions about new product introduction and production capacity. Their econometrics-based forecasting techniques were not able to capture the ups and downs, and particularly the turning points, of the extremely cyclical aircraft market on which they depended. When the analysis was first performed, the order rate had reached a level never before seen in the industry. Key questions for Airbus were: Is the market at its peak? If not, when will it peak and when will the next downturn occur? How long will it last? How much new capacity should we add? And how sensitive are

these outcomes to potential deregulation of the European airline sector, increasing airport congestion, and future economic and fuel price trends?

To help, PA developed a system dynamics simulation model of the worldwide market for air transport and aircraft manufacturing to forecast aircraft order cycles. The architecture of this model is shown in Figure 10. The model contains the key elements that drive aircraft order cycles and the interactions between them for the major regions of the world and the major size categories of aircraft.

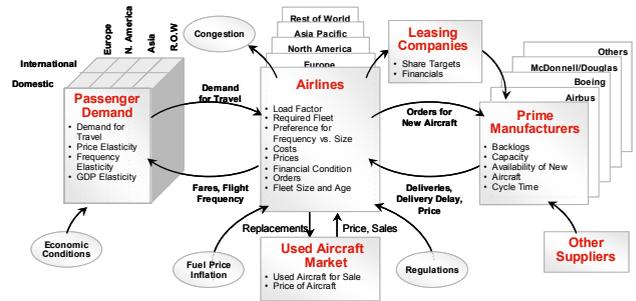


Figure 10: The Model Represents the “Supply Chain” From Passenger Demand Through to Manufacturing

The model successfully reproduced the cyclical dynamics of the market, and generated an accurate mid-term forecast of the order rate (including new distortions resulting from the advent of the aircraft leasing companies).

With a clearer view of what the future would bring, Airbus saved billions by avoiding undesirable and costly expansions in production capacity, enabling it to focus instead on reducing its manufacturing cycle time and production costs. A full description of this case can be found in Lyeis (2000).

4.2 London Underground: Aiming for Restructuring Success

After decades of public under-investment, London Underground (LUL) was directed by government in mid-1997 to explore restructuring options to bring in private sector funding. LUL sought to strike a good balance between financial, service delivery and safety performance, and to implement the mandated restructuring with the least service disruption. To evaluate their options, PA worked with LUL to develop a comprehensive system dynamics simulation model of the Underground’s operations, its customers and their choices, and competing transportation modes.

The model provided a rigorous, objective means of quantifying the risk/benefit trade-offs associated with each option by simulating how future system performance would evolve under each option. Key variables reviewed included impacts to riders (e.g., journey time, ambience, perceived safety, and number of journeys), LUL staff numbers, quantity of service delivered, and social benefit

delivered. One of the key insights from this work was that the quality of implementation matters more than which restructuring option is selected. Since the UK government selected the Public-Private Partnership (PPP) structure, the model has been used systematically to improve the chances of a good outcome, for example by:

- Identifying the aspects of PPP implementation that would determine its success or failure
- Testing the performance regime and refining its implementation
- Sharing analytical lessons with bidders for the new businesses to educate them about the workings of the Underground
- Enhancing LUL's understanding of the bids received, by identifying implicit bid assumptions and testing their robustness

London Underground has used this model to support a broad range of strategic questions over the course of several years. A more extensive description of work to support the restructuring of LUL is given in Mayo, Callaghan, Dalton (2001). Mayo, Callaghan, Dalton (2003) contains a description of other strategic and operational uses of the model.

4.3 U.S. Maritime Administration: Improving Performance of US Shipping Firms

In a climate of declining U.S. carrier market shares in international ocean shipping, unstable profits, and some company bankruptcies -- all in an environment of stiff foreign competition, uncertain economic outlook, increasingly diverse technological alternatives, and changing government regulations -- the U.S. Maritime Administration (MarAd) sought a means to bolster the state of U.S. container shipping. MarAd wished to develop a capability for ocean shipping business managers and government planners to evaluate more accurately, consistently, and comprehensively different strategies for improved financial and market share performance.

MarAd provided 'seed funding' for PA to work with a US carrier -- Lykes Bros Steamship Company -- to design and implement a dynamic simulation model that would provide such a capability. The analytical tool developed could recreate 10 years worth of performance of individual carriers and groups of carriers on a trade route, and of projecting performance under a set of assumed conditions ten years or more into the future. Using the model, users at Lykes Bros and MarAd posed and gained insight into questions in two broad areas.

First, how do a carrier's own management policies impact carrier performance? For example:

- How would a carrier's short-term and long-term performance on a particular trade route be affected by policy changes regarding ship acquisition, lay-up and scrapping, participation in gov-

ernment assistance programs, rate setting, country of registry, conference membership, and financial structure?

- What are the effects in terms of market share, profits, and operations?
- What are the implications of various responses to the actions of competitors?

And second, how do government programs and policies impact carrier performance? For example:

- How would carriers on a particular trade route be affected by changes in ODS, Title XI, cargo preferences, and bilateral agreements?
- How would the short-run impacts differ from what would happen in the long-term?
- How would these consequences be affected by various international economic and political scenarios?

The dynamic model developed to address these policy issues contains hundreds of equations which represent the acquisition, deployment, and scrapping of vessels; the competition for trade among routes, types of vessels, and carriers; financial flows; the managerial decisions of ship owners and operators; and the prevailing economic and political environment.

4.4 Transmanche Link: Diagnosing Performance on the Cross Channel Tunnel Project

The Channel Tunnel Project was an ambitious development effort to link the United Kingdom to the rest of Europe via a rail link running under the English Channel. It was a complex undertaking, presenting significant engineering and stakeholder management challenges. "The Chunnel" was organized as a complex set of interdependent sub-projects, which included Target Works (civil works), terminals on the UK and French sides of the channel, and Fixed Equipment (installed inside the tunnels).

The project had evolved very differently than originally envisaged, and a significant backlog of commercial claims had built up by the time the analysis was begun. A large number of unplanned events and conditions had occurred (e.g. scope growth, poor ground conditions, rolling stock delays), and a variety of customer, contractor and third party actions had without doubt contributed to the delay and cost growth experienced on the project. However, there was no way of linking cost and schedule growth back to these problems, or to understand how to attribute this growth to specific problems. Commercial complications also existed due to prior "settlements", with resulting "re-baselining" of the project and confusion about what was really settled. The situation required supporting analytics to be transparent, auditable, and easily communicated to a non-technical, principally legal audience.

PA worked with Transmanche Link (TML) to develop a system dynamics model that captured the interrelated dynamics of the entire project. The model was used to diagnose and attribute responsibility for cost and schedule growth to TML, the customer Eurotunnel and third parties by simulating the project, *with and without* the unplanned events and conditions. The simulation analysis helped TML by:

- Establishing clear cause-and-effect links between the many unplanned events and conditions and the resulting dynamics on the project
- Quantifying the cost and schedule impact of each unplanned event and condition (including how that quantification depended on conditions experienced during the remainder of the project)
- Supporting UK Terminal and Fixed Equipment claims by TML
- Helping establish TML’s defense against Euro-tunnel claims of specific instances of TML mis-management

The end result was a fair settlement for TML.

5 COMPARING SYSTEM DYNAMICS TO DISCRETE EVENT SIMULATION

In this section, we summarize how system dynamics (SD) compares to discrete event simulation (DES) along a range of fundamental dimensions. Table 1 provides the detail of the comparison (which is not intended to represent an exhaustive evaluation). The text below addresses some of the most important of these differences.

Use of data is one of the most significant differences between the two methods. While DES is dependent on the availability of rich and detailed data as inputs to produce a simulation, SD uses data in three key ways:

1. To initialize the simulation at the start. Thereafter, the SD equations step through time, in essence “boot strapping” themselves on the calculations in the previous time step.
2. To represent any exogenous variables. There are typically relatively few of these within a SD model.
3. As a check on model behavior. Simulated outputs are compared and calibrated against all known data.

Another key difference in the use of data is the explicit collection of first-hand knowledge and other qualitative information that is used alongside measurable time-series data as another consistency check on the SD model’s behavior. The elicitation of such knowledge has been the subject of considerable study by system dynamics researchers (see for example Ford and Sterman 1998).

The breadth of model scope can frequently differ between the two methods, which is related to the level of detail at which key operations and relationships are considered. As shown earlier in Figure 10, SD frequently examines systems with very wide boundaries – but at a correspondingly more aggregate level of detail. DES may

Table 1: Summary Comparison of System Dynamics to Discrete Event Simulation

| | System Dynamics | Discrete Event Simulation |
|---|--|---|
| Use of data | Data inputs used to initialize simulation starting point and to represent exogenous variables (e.g. GDP growth time series). Other data, both measurable time series and qualitative, used to verify simulation behavior. Data does NOT drive the model. | A rich data set, containing information about desired attributes of the processes, is required to describe entities and processes. Model is driven by the underlying data set. |
| Model boundary | Can be limited to smaller areas (e.g. a department with firm) or extremely broad (e.g. an industry, with representation of company, customers, competitors, suppliers, regulators, etc.). | Typically limited by practical constraints imposed by the number of events that can be represented. These are driven by e.g. level of abstraction, numbers of entities, attributes, processes, reporting periods. |
| Feedback loops | The model is made up of cause-effect relationships that form numerous interlinked feedback loops. These operate within as well as across components of the system. | Limited generally to process-specific issues (e.g. rework faulty components). There is no wider system level feedback represented. |
| Representation of 'soft' factors | Can represent soft factors (e.g. public perception of service quality, staff morale) in the same way as any other variable within the feedback structure. Typically validated by first-hand knowledge of people with working knowledge of the system under study. | Soft factors must be quantified with rich data to be included. Most models omit social and psychological factors. |
| Level of detail | Usually aggregates items that share the same underlying drivers. Emphasis is on using the simplest structure needed to explain the behavior of the system. When micro causes give macro effects, this is represented by an aggregation equation. | Usually detailed down to the unit-of-work, or time-of-day level. When micro causes give macro effects, this is represented by simulating at the micro level. |
| Nature of "flow" | Uses continuous flows | Can use either continuous or discrete flows or a mixture. |
| Validation/calibration | Possible and important. Calibration here involves testing that the feedback structure is capable of recreating a period of historical performance (typically 3-5 years) on broad set of measures (both measurable and qualitative) without direct computational use of the data. | Possible and important. Calibration here involves testing that a known set of data inputs is capable of reproducing a known set of outputs. |
| Simulation length | May be short with very small delta time steps (e.g. period of hours required for a drug to take effect in the body, simulated in intervals of seconds) or long with appropriately larger delta time steps (e.g. a thirty year contract period, simulated in intervals of roughly every three weeks). | May be short or long. Typically restricted to shorter simulation lengths because of difficulty in getting rich data that is valid over longer periods. |
| Visualisation of simulation and results | Has not been a focus of high-end system dynamics simulation packages to date. Simulation results are typically viewed upon completion of the simulation. | Supported well by high-end tools. Can often view in a highly graphic way the course of events as they unfold throughout the simulation (e.g., the movements of airport passengers throughout the terminal). |
| Representing complex entities and locally complex non-linear interactions | Difficult. | Easier, although the complex behaviors are hard to model in any framework. |
| Spatial dimensions | Not supported well by standard tools. | Supported well by high-end tools. |
| Averaging over "possible futures" | Often inherent in model formulations, with one simulation representing a 'base case' | Often no simulation is a natural base case, and averaging is performed by running multiple shorter simulations. |
| High-impact stochastic events | Rarely modeled | Commonly modeled |
| Conceptual and qualitative modeling | Acknowledged as important and usually treated as such | Acknowledged as important but sometimes ignored to give a tractable model. |

cover a narrower range of activities within the model boundary, but will therefore enable examination of the underlying operations in a highly detailed manner. This combination – scope and level of detail – is a key factor in determining the modeling approach that is most appropriate to a particular problem.

Calibration and validation are important and possible for both SD and DES models. The difference here comes in how calibration is demonstrated. For an SD model, the calibration test involves verifying that the equation structure can recreate a period of known historical performance, typically 3-5 years. It must achieve this simultaneously on many measures without direct use of the data. For DES, where the model must be driven by input data sets, the test primarily involves reproducing a set of known outputs using a set of known inputs.

It is also worth noting the superiority of simulation visualization that can be achieved by use of high-end DES simulation packages such as Arena. Such visualization in practice is highly engaging. High-end SD software does not currently offer the ability to see in simulated time e.g. people moving around a station or a ship being constructed in the same way.

Other key differentiators cited in Table 1 include the degree of representation of feedback loops (SD majors on these at all levels, while DES permits some limited representation of simple feedback), representation of “soft” factors (SD permits inclusion of such factors in the same way

as any other variable in the model, while DES requires quantitative data to incorporate soft factors), the nature of the underlying “flows” (SD is continuous, DES may be continuous, discrete or a mixture), and simulation length (SD may be long or short depending on need, in DES length is typically determined by the period of availability of valid data), as well as several others.

6 SOME GUIDANCE ON SELECTING A MODELING APPROACH

Selecting the “right approach for the right purpose” is perhaps the most critical determinant of a successful modeling effort and could easily be a paper topic unto itself. While this paper has focused its discussion on SD and DES, there are other approaches, including the use of spreadsheets and various types of optimization algorithms, that are often a better choice for addressing particular types of transport, supply chain and logistics issues. Selecting the right approach or collection of approaches is often made challenging by the propensity for modelers to view every problem through the lens of the technique with which they are most familiar. This can especially blind the modeler to potential solutions that involve a combination of approaches. For example, to create the business case for a new set of operations one might:

- Use a high level SD model to design the operations to fit within the overall strategy and positioning of the company (e.g., understand the nature of the key interrelationships between the proposed and current operations, identify critical success factors for successful launch, etc.)
- Apply optimization techniques to identify the ideal mix of infrastructure (number of sites, locations, functions, links between these, etc.)
- Develop a DES model to test and develop the operational rules that will govern the new operations (e.g. replenishment rules, production priorities, transport policies, etc.)
- Create a spreadsheet model to combine and present the modeling results in financial terms (e.g. calculate total costs and capex requirements, analyze cash flow, etc.).

In practice, using a mix of models is an iterative process whereby results from one model may inform the inputs to another and vice versa. It is not possible to treat all the elements involved in determining the best approach in great detail here. Fundamentally though, making a good choice follows these steps:

- Examine the problem to determine its characteristics and define the key questions that the analysis must address. The types of questions that will help to pin down the requirements are illustrated in Figure 11.

- Match the resulting problem characteristics and analysis questions against a range of approaches, considering both their requirements (e.g. data) and capabilities (e.g. accommodation of required model boundary). A key issue to consider at this stage involves ensuring that the selected approach can produce answers in the desired terms. Is it good enough to have answers in quite aggregate terms (e.g. a group of “average” cases with similar characteristics) or is our interest more in understanding and tracking individual units throughout the system to determine performance distributions (e.g. tracing unique cases throughout the system to be able to report that 85% of these complete the first stage within 8 minutes)?
- Consider whether an approach that combines several techniques can increase the rigor or confidence of the analysis.

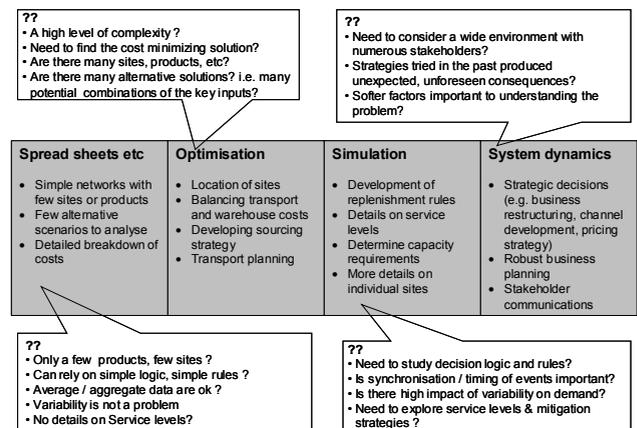


Figure 11: Asking a Series of Questions Can Help Point the Way to the Best Approaches

The outcome from these steps will in many cases yield a clear choice. For instance, when dealing with a potentially broad model boundary, a complex environment, with numerous stakeholders, and ‘soft’ factors are clearly important to understanding the behavior of the system, system dynamics is probably the best option. If the need is instead to simulate and understand local operational-level details and to follow the progress of unique items throughout the system, SD would likely be ruled out. Instead, DES would appear to meet these requirements perfectly. There will also be instances when the choice is less immediately obvious. In such cases, the decision is frequently driven by other considerations, such as data availability.

7 SUMMARY

We have provided an overview of the key characteristics of the system dynamics method and illustrated its usefulness to addressing strategic level issues using the four case ex-

amples with transport sector organizations. We have also compared system dynamics to discrete event simulation along the dimensions of data use, model boundary, level of detail represented, and many others. Finally, we have offered some guidance for selecting among potential analysis approaches, in particular a series of basic steps to help identify the approach that will best satisfy the needs of the problem.

ACKNOWLEDGMENTS

The case examples described within this paper are the product of the work of many colleagues (both current and former) within the Decision Sciences Practice of PA Consulting Group (the former Pugh-Roberts Associates). The full teams involved in the referenced assignments are too numerous to mention here, but key leaders of the work included Ken Cooper, James Lyneis and Bill Dalton.

REFERENCES

- Eubanks, K., L. Yeager. 2001. An Introduction to Jitia: Simulation Software Designed for Developing Large System Models. In *Proceedings of the 2001 System Dynamics Conference*.
- Ford, D. N. and J. D. Sterman. 1998. Expert Knowledge Elicitation to Improve Formal and Mental Models. *System Dynamics Review* 14(4): 309-340.
- Huber C., F. Cooke, J. Smith, M. Paich, N. Pudar, V. Barabba. 2002. A Multimethod Approach for Creating New Business Models: The General Motors On-Star Project. *Interfaces* 32(1):20-34.
- Lyneis, James M. 1999. System Dynamics for Business Strategy: A Phased Approach. *System Dynamics Review* 15(1):1-34.
- Lyneis, James M. 2000. System Dynamics for Market Forecasting and Structural Analysis. *System Dynamics Review* 16(1): 3-25.
- Mayo, D. D., M. J. Callaghan, W. J. Dalton. 2001. Aiming for Restructuring Success. *System Dynamics Review* 17(3): 261-289.
- Mayo, D. D., M. J. Callaghan, W. J. Dalton. 2003. Steering Strategic Decisions at London Underground: Evaluating Management Options with System Dynamics. In *Proceedings of the 2003 Winter Simulation Conference*, ed. S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.
- Sterman, J. D. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. New York: Irwin/McGraw-Hill.

AUTHOR BIOGRAPHIES

DONNA D. MAYO is a member of PA Consulting Group's Decision Sciences Practice. During 10 years with PA, she has applied system dynamics to address issues of business strategy, complex program management and litigation support in the transportation, aerospace, shipbuilding, software development and telecommunications industries. Donna holds a master's degree from MIT Sloan School of Management and a bachelor's degree from Yale University. Her email address is <donna.mayo@paconsulting.com>.

KNUD ERIK WICHMANN has been acknowledged as a global expert in the area of modeling and simulation for a decade. Knud Erik joined PA in December 2002, and has been a Management Consultant since 1988. As head of PA's Copenhagen based Centre of Excellence for Modeling and Simulation within the global Decision Science practice, he leads a team of highly trained consultants with focus on developing and applying quantitative analytical methods (such as discrete event simulation) and business intelligence applications, working with clients and colleagues globally. Prior to PA, Knud Erik was a Partner in PricewaterhouseCoopers Management Consultants and global leader of PwCs Centre of Excellence for Modelling and Simulation. He has led more than a hundred assignments in different industries including Logistics and Transportation (airports, shipping, rail, harbor, postal etc), Retail, Government, Industrial Production and Energy and Mining. Knud Erik was researcher and associate professor at the Technical University of Denmark from 1981 to 1987. Based upon insights from this research he founded his own Simulation company, SIMOS, in Denmark in 1988. After 4 years of building the company, SIMOS was acquired by Coopers and Lybrand merging with Pricewaterhouse in 1998. His email address is <knud.erik.wichmann@paconsulting.com>.