Lecture Notes in Social Networks

Jim Duggan

System Dynamics Modeling with R

Springer

Lecture Notes in Social Networks

More information about this series at http://www.springer.com/series/8768

Jim Duggan

System Dynamics Modeling with R

Springer

Jim Duggan
School of Engineering and Informatics
National University of Ireland Galway
Galway
Ireland

ISSN 2190-5428 ISSN 2190-5436 (electronic)
Lecture Notes in Social Networks
ISBN 978-3-319-34041-8 ISBN 978-3-319-34043-2 (eBook)
DOI 10.1007/978-3-319-34043-2

Library of Congress Control Number: 2016939926

Printed on acid-free paper

This Springer imprint is published by Springer Nature
The registered company is Springer International Publishing AG Switzerland

To Marie, Kate and James

Foreword

Since the emergence of system dynamics (SD) in the late 1950s, a range of literature has been published describing the methodology and detailing the best practices in model formulation together with its application to an ever-increasing span of domains. It would be true to say that the aspiring practitioner now has an enormous array of choices through which their competence in SD can be developed and broadened, far more so than faced those of us seeking to hone our skills in the 1970s and 1980s. Not only has the subject matter extended beyond the creation of formal simulation models to embrace the diagrammatic tools inherent in the qualitative aspects of the practice of SD (usually referred to as systems thinking) but also the simulation toolset on offer has similarly proliferated.

The student intending to become proficient at model formulation and execution is now faced with choices centered on the software platform to adopt. These extend from bespoke SD software to hybrid modeling tools which allow the user to code discrete-event and agent-based features in addition to SD. A software learning curve looms. Attempts to embrace SD modeling in, originally, general-purpose programming languages and, latterly, spreadsheets have not secured a significant user base.

In this new textbook, Jim Duggan breaks fresh ground in the practice of SD modeling by showing how it can be enabled through the *R* software environment for statistical computing and graphics. This software first emerged in the early 1990s, and it is chastening to realize that the scholarly endeavor inherent in this book could not have been mounted a mere twenty odd years ago. Being open source means of course that the *R* software is free, and thus, there exists significant potential to attract new students of SD as a consequence of this work. Not only that, but those whose predominant expertise is in the use of *R* for some other (data science) purpose could now find themselves being drawn into a whole new field as a result of this contribution.

The author's intent is clear: The book is devoted solely to the *formulation* of SD models. It is pitched at a technical level designed to showcase best practice in the craft of SD modeling with its underpinnings in integral calculus. Coverage firstly embraces the foundational aspects, followed by applications to various domains including economic growth, health care, and epidemiology. The final section is devoted to some technical aspects of SD modeling which embody mathematical and statistical methods and which are largely missing in other SD texts. Such aspects embrace model output analysis techniques, including statistical screening introduced by Ford and Flynn in 2005, as well as model calibration to reported data. These powerful and relatively new features of SD modeling are easily addressed using *R* and, of necessity, harness the strengths of its visualization features. Indeed, *R* is currently cited in the *System Dynamics Review* "Notes for Authors" as the recommended platform for producing publication quality graph plots.

The author is a current member of the Policy Council of the System Dynamics Society and serves on the editorial board of the *System Dynamics Review* as an Associate Editor. He has also acted as a Thread Chair for the methodology stream at system dynamics conferences. All this esteem stands as a testimony to his expertise in penning this welcome new perspective addressing the foremost component of SD practice—how to put together a set of model equations which reflect a dynamic system and which can then be used to explore its behavior over time. It is a valuable and significant addition to the SD literature.

Brian Dangerfield
Department of Management
University of Bristol, UK

Preface

A model should always be created for a purpose.

Jay W. Forrester, Urban Dynamics (1969), p. 113

System dynamics is a modeling approach used to construct simulation models of social systems, and these computerized models can then support policy analysis and decision making. This simulation method is based on calculus, and models of real-world dynamic processes are constructed using integral equations.

A key strength of system dynamics is that the simulation models provide an integrated view across organizational boundaries and functional areas, and so support a *joined-up thinking* approach to problem solving. System dynamics also provides a unique way of viewing social systems. This is known as the *feedback perspective,* where cause and effect between different system elements can be formally analyzed to help explain system behavior, and so generate insight into how to make better decisions. System dynamics has been successfully applied across a range of application areas, including complex and challenging domains such as project management, health care, manufacturing, epidemiology, and climate change.

The aim of this book was to provide readers with a practical understanding of system dynamics, so that they are in a position to design and implement simulation models in their chosen problem area. The book is structured into three thematic areas.

- *Foundations* (Chaps. 1–2). Chapter 1 provides an introduction to modeling and system dynamics. Foundational system dynamics concepts are presented, including simulation based on stocks, flows, and feedback. Models are solved using calculus, and the principles of numerical integration are presented. Chapter 2 is a primer in the open source R programming language and environment. R supports statistical computing and data analysis, and also has libraries for numerical integration. Important R concepts such as vectors, data frames, and functions are covered, and a system dynamics model is implemented in R.

- *Dynamic models of social systems* (Chaps. 3–5). Chapter 3 introduces a method for representing cause and effect equations in system dynamics. It then presents three different growth models in system dynamics, including s-shaped growth, an economic growth model, and a non-renewable resource growth and decline model. Chapter 4 introduces delays, which are features of social systems, and also the stock management heuristic for regulating important stock resources. A healthcare model combining three sectors, population, delivery, and general practitioner supply is specified, and this demonstrates how system dynamics can be applied to *joined-up* policy planning issues. Chapter 5 presents diffusion models for infectious disease transmission and control and includes the classic susceptible–infected–recovered (SIR) model. This is extended with a disaggregated model and highlights the power of R to simulate, using matrix manipulation, inter-cohort disease transmission dynamics.
- *Model testing and analysis* (Chaps. 6–7). Chapter 6 focuses on model testing and summarizes the system dynamics approach to validation. Practical methods for testing models are presented and implemented using R's unit test framework. Chapter 7 introduces a formal approach to feedback loop analysis. It presents a valuable parameter analysis method known as statistical screening, which uses a base set of sensitivity simulation runs to generate a data set that is analyzed using statistical methods. The results of this analysis then highlight those parameters that have the greatest influence on a variable's trajectory, which can enhance the overall policy design process and provide decision makers with more information on potential intervention strategies. This chapter also describes the important area of model calibration, where key parameters can be estimated in order to find the best fit of historical data to the underlying model structure.

System Dynamics and Calculus

System dynamics is grounded in calculus, which is the study of how things change over time. Calculus is described by Strogatz and Joffray (2009) as *perhaps the greatest idea that humanity has ever had*. Calculus allows us to communicate at the speed of light, build bridges across great divides, and take action to halt the spread of epidemics. Sterman (2000) observes that the study of calculus can be quite daunting, as the use of unfamiliar notation, and a focus on analytical solutions, can deter many people.

However, integration is an intuitive concept that can be understood without reference to formal mathematics, and system dynamics uses integration to model things that change over time. For example, system dynamics simulation models that generate projections for population levels in cities, prevalence values for infectious disease outbreaks, and inventory levels in global supply chains all use integration as the simulation method. In Chap. 1, the process of integration is summarized, with an initial look at *analytical* solutions, before focusing on *numerical* approaches, which are widely used in system dynamics simulation tools.

Related System Dynamics Texts

This book provides a complementary perspective to the range of system thinking and system dynamics textbooks, which include the work of Sterman (2000), Morecroft (2007), Warren (2008), Ford (1999), and Maani and Cavana (2007). This book's focus is on quantitative stock and flow models, and, similar to Meadows (2008), does not address the use of qualitative causal loop models. The motivation here is to focus on the set of core modeling concepts and constructs that can provide the necessary practical knowledge for readers to build system dynamics models.

Because of this, a number of areas covered by other texts, and by ongoing research in the *System Dynamics Review*[1] are not covered. These include model structures such as co-flows, bounded rationality, and supply line management; machine learning methods for analyzing system dynamics output, for example, techniques such as classification and clustering which can be used to explore the policy space (Kwakkel and Pruyt 2013); advanced analytical methods such as calibration, estimation, decision support, and optimization, which can support the model building process (Rahmandad et al. 2015); and formal model analysis using mathematical approaches such as eigenvalue and eigenvector analysis, which provide powerful formal methods to analyze the structure and behavior of system dynamics models (Duggan and Oliva 2013).

Related Complexity Work in Other Disciplines

In system dynamics, the definition of a complex system refers to a high-order, multiple-loop nonlinear feedback structure (Forrester 1969), and all social systems can be viewed from this perspective. The *order* is simply the number of stocks (or states) in the system, for example, Forrester's urban model is twentieth order. *Multiple-loop* reflects the presence of circular causal links between state variables, and the interaction among these loops can explain a complex system's behavior. It is important to acknowledge complementary computational methods for exploring and understanding complex systems. While system dynamics operates at an aggregate level that captures feedback, other methods, such as agent-based modeling, view a complex system from an individual perspective. Agents (e.g., individuals) are represented in a spatial network structure and make decisions based on

[1] http://onlinelibrary.wiley.com/journal/10.1002/(ISSN)1099-1727.

local information (Railsback and Grimm 2011). Epstein (2006) describes the classical agent-based experiment as follows:

> Situate an initial population of autonomous heterogeneous agents in a relevant spatial environment, allow them to interact according to simple local rules, and thereby generate—or "grow"—the macroscopic regularity from the bottom up.

This definition concisely summarizes the agent-based modeling perspective. By focusing on an autonomous agent (which is usually a model of a person or an organization), individual differences are captured and codified. For example, an agent-based model of infectious disease transmission would include a profile of different individuals (infants, young children, teenagers, adults, and elderly), their disease status (susceptible, infected, or recovered), a map of their contact network (family contacts, friendship links, and workplace connections), and a model of disease transmission based on the frequency of interactions between infected and susceptible people. From these interactions, an overall pattern of behavior emerges, and the outbreak of a disease can be traced, over time, through a causal chain of networked connections.

While a discussion of agent-based modeling is outside the scope of this text, there are parallels between system dynamics and agent-based modeling. Specifically, the disaggregated disease transmission model in Chap. 5, where the population is subdivided into age cohorts, has parallels with the agent-based perspective, and readers looking to bridge from system dynamics to agent-based modeling are encouraged to use the infectious disease case as an exemplar, and also consider other works that have explored similarities between the two methods, for example, the study by Rahmandad and Sterman (2008).

Why R?

Published system dynamics texts use the excellent set of available special-purpose modeling software to implement system dynamics models. In this text, an open source approach is used, and system dynamics models are implemented using R. R is a powerful programming language designed to analyze and interpret data, and it has an extensive set of open source libraries that can support decision analysis. This includes the **deSolve** library (Soetaert et al. 2010), which supports numerical integration using a range of numerical methods. There are three reasons for using R for system dynamics modeling:

- R provides a comprehensive set of statistical and optimization functions that can be used to analyze and calibrate simulation output. For example, in Chap. 7, the statistical screening method for system dynamics models (Ford and Flynn 2005) is implemented, as is a calibration method for data fitting. R also has a differential equation solver that can be used to implement system dynamics models.

- R has a powerful visualization library that can be used to present the behavior space of system dynamics models, and so present policy scenarios in a convincing manner to decision makers.
- R is a leading platform for data science methods such as regression and classification to support data analytics. By also supporting implementation of system dynamics models, it means that analysts can adopt multimethod approaches in addressing complex problems.

Model Catalog

One of the most enjoyable aspects of system dynamics modeling is that the method can be applied in a range of domains. Therefore, modelers are presented with opportunities to work across disciplines and interact with experts in a range of domains, on challenging policy problems. The models presented in this text illustrate the breadth of application of system dynamics and include the following:

- Epidemiology, with a focus on a contagious disease model in Chap. 5, and an interesting extension of this to a disaggregate form, based on a vectorized R implementation.
- Health systems design, which, in Chap. 4, provides a joined-up model comprising population demographics, a supply chain of general practitioners, and a demand-capacity model of general practitioner services to overall population.
- Economics and business, ranging from simple customer model in Chap. 1, and onto models of limits to growth, capital investment, and the impact of non-renewable resources on growth, all of which are covered in Chap. 3.

Intended Audience

This book can be used as a supporting text for courses in system dynamics, simulation, complexity, and mathematical modeling. Previous knowledge of basic calculus and an understanding of algebra would be an advantage, although in system dynamics, the stock and flow notation is intuitive and practical. The book also can be used as a reference for consultants and engineers who design and implement system dynamics models and plan to align their work with data science methods such as regression and classification. A full set of model and code examples, and lecture slides, is available online at https://github.com/JimDuggan.

Feedback

Comments, suggestions, and critiques are most welcome, including ideas for further examples that could be added to the online resource. Feedback can be emailed to jim.duggan@nuigalway.ie.

Acknowledgements

There are many individuals I would like to acknowledge who have contributed to my knowledge of systems thinking, system dynamics, and computer science. These include lecturers in Industrial Engineering in NUI Galway, who provided me with an early career insight into the decision support potential of management science, operations research, systems thinking, and simulation; colleagues in the College of Engineering and Informatics in particular, Gerry Lyons, Owen Molloy, and Enda Howley, for their excellent collaborations, and their shared enthusiasm for interdisciplinary research; and graduate research students for their innovation, ideas, and willingness to explore exciting research challenges at the intersection of system dynamics, data science, computer science, and complex social systems.

Thanks to my colleagues—from all parts of the world in the System Dynamics Society. The society provides a wonderful collegial space for sharing exciting ideas, investigating challenging research questions, and, of course, exploring simulation and modeling through stocks, flows, and feedbacks. In particular, thanks to Brian Dangerfield (University of Bristol), Pål Davidsen (University of Bergen), Bob Cavana (Victoria University of Wellington), and Rogelio Oliva (Texas A&M University) for their insights into system dynamics, their enthusiasm for the field, and their excellent advice on system dynamics research. Thanks also to the staff at Springer: Stephen Soehnlen, Senior Publishing Editor, for providing me with the opportunity to propose and write this book; and Pauline Lichtveld, Production Department, for her assistance in completing the production process. Finally, a special thank you to my family for their encouragement, inspiration, and support.

Galway, Ireland Jim Duggan
May 2016

References

Duggan J, Oliva R (2013) Methods for identifying structural dominance—introduction to the model analysis virtual issue. Syst Dyn Rev (Virtual Issue). http://onlinelibrary.wiley.com/journal/10.1002/(ISSN)1099-1727/homepage/VirtualIssuesPage.html

Epstein JM (2006) Generative social science: Studies in agent-based computational modeling. Princeton University Press. Chicago

Ford FA (1999) Modeling the environment: an introduction to system dynamics models of environmental systems. Island Press

Ford A, Flynn H (2005) Statistical screening of system dynamics models. Syst Dyn Rev 21:273–303

Forrester JW (1969) Urban dynamics. Pegasus Communications, Waltham, MA

Kwakkel JH, Pruyt E (2013) Exploratory modeling and analysis, an approach for model-based foresight under deep uncertainty. Technol Forecast Soc Change 80(3):419–431

Maani K, Cavana RY (2007) Systems thinking, system dynamics: managing change and complexity. Prentice Hall

Meadows DH (2008) Thinking in systems: a primer. Chelsea Green Publishing

Morecroft J (2007) Strategic modelling and business dynamics: a feedback systems approach. Wiley

Railsback SF, Grimm V (2011) Agent-based and individual-based modeling: a practical introduction. Princeton University Press

Rahmandad H, Oliva R, Osgood N (eds) (2015) Analytical methods for dynamic modelers. MIT Press, Cambridge

Rahmandad H, Sterman JD (2008) Heterogeneity and network structure in the dynamics of diffusion: comparing agent-based and differential equation models. Manag Sci 54(5):998–1014

Soetaert KER, Petzoldt T, Setzer RW (2010) Solving differential equations in R: package deSolve. J Stat Softw 33

Sterman JD (2000) Business dynamics: systems thinking and modeling for a complex world. Irwin/McGraw-Hill, Boston

Strogatz S, Joffray D (2009) The calculus of friendship: what a teacher and a student learned about life while corresponding about math. Princeton University Press

Thompson KM, Tebbens RJD (2008) Using system dynamics to develop policies that matter: global management of poliomyelitis and beyond. Syst Dyn Rev 24(4):433–449

Warren K (2008) Strategic management dynamics. Wiley, Chicago

Contents

Chapter 1
An Introduction to System Dynamics

Everything we do as individuals, as an industry, or as a society is done in the context of an information-feedback system.
Jay W. Forrester, Industrial Dynamics (1961), p. 15.

Abstract This chapter presents important concepts underlying the system dynamics modeling method. Following an initial definition of the term model, a summary of a successful system dynamics intervention is described. The key elements of system dynamics—*stocks and flows*—are explained. The process for simulating stock and flow models—*integral calculus*—is described, with an example of a company's customer base used to illustrate how stocks change, through their flows, over time. A summary of dimensional analysis for stock and flow equations is provided before the second feature of system dynamics modeling—*feedback*—is presented. The chapter concludes by summarizing the system dynamics methodology, which is a five-stage iterative process that guides model design, development, test and policy design.

Keywords Models · Stocks · Flows · Feedback · Integration

Models

Pidd (1996, p. 15) defines a model as:

> an external and explicit representation of part of reality as seen by the people who wish to use that model to understand, to change, to manage and to control that part of reality.

This is an insightful definition that also applies to system dynamics. The model building process focuses on a *part of reality* that needs to be understood and managed, and creates an *external and explicit representation,* in the form of a model, of this reality. This reality could be an organization faced with declining market share, a public health agency confronted by an infectious disease outbreak, or governments challenged by increased levels of carbon in the atmosphere, with

J. Duggan, *System Dynamics Modeling with R*, Lecture Notes in Social Networks,
DOI 10.1007/978-3-319-34043-2_1

the resulting rise in mean global temperatures. In these scenarios, decision makers are faced with a complex, and highly interacting, social system. Models provide a basis for decision makers to understand their world as an interconnected system, and to test out the impact of policy interventions *in silico*. Understanding leads to insight, and an opportunity to change, manage and control the system of interest.

In order for a model to be useful to decision makers, it must provide some view on future behavior, and Meadows et al. (1974) provide a valuable classification of the types of outputs models can provide:

- *Absolute, precise predictions*, for example, when and where will the next solar eclipse be observable?
- *Conditional, precise predictions,* for example, if a cooling systems fails in a nuclear power plant, what will be the maximum pressure exerted on the reactor's containment vessel?
- *Conditional, imprecise projections of dynamic behavior*, for example, if an infectious disease spreads through a population, what is the likely future burden of demand on intensive care facilities one month from the outbreak date?

Because system dynamics is primarily a technique for business and policy simulation modeling (Homer 2012), its primary focus is on the third class of model: those simulation models that provide conditional, imprecise projections of dynamic behavior. This is because social and business systems are by their nature unpredictable in the absolute sense (Meadows et al. 1974). So while *all models are wrong* (Box 1976), as they cannot generate precise point-predictions of future events in social systems, the challenge is to create *models that are useful* through extensive testing, benchmarking against available data, and continual iteration between experiments with the virtual world of simulation and the real world (Sterman 2002). System dynamics has a rich tradition of creating useful models across many disciplines, and, to illustrate this, an application of system dynamics to public health policy is presented.

System Dynamics in Action: Population Health Policy

In their paper—*Using system dynamics to develop policies that matter: global management of poliomyelitis and beyond*—Thompson and Tebbens (2008) document their award-winning research which demonstrates how system dynamics impacted global health policy analysis. This supported the Global Polio Eradication Initiative (GPEI) to eradicate wild polioviruses, which aimed to replicate the success of the eradication of smallpox in 1979 (Breman and Arita 1980). Initial results of this initiative, based on an intensive vaccination campaign, led to a reduction from 350,000 global annual cases to 1000 cases per year.

However, the eradication project faced funding shortfalls during 2002–3, and the allocation of vaccination resources prioritized endemic countries where the virus circulated, leaving other countries vulnerable. This containment policy inevitably led to further outbreaks. While additional investment was made to regain lost ground, a new policy debate started that questioned the feasibility of eradication, and suggested that the guiding policy should switch to one of control, as this could save resources while maintaining outbreak cases at manageable low levels.

The authors proceeded to evaluate the impact of this proposed policy change, and assess the economic impact, and potential disease burden, of these two distinct policy options. Core to the analysis was a system dynamics disease outbreak model. This model represented the population as a set of stocks and flows, where people were classified as being susceptible to, infected with or recovered from the wild poliovirus. The stock and flow model distinguished between 25 different age groups. This model was also informed by their prior studies related to risk management, including a cost-based analyses of tradeoffs associated with outbreak response.

As a result of the model building process, the authors highlighted the impact of *wavering*. This describes a scenario whereby in the context of successful vaccinations comes the perception that a high level of continued investment in vaccine administration is not required. This view was represented in the system dynamics model. Focusing on two Northern Indian states, two policy options were evaluated. The first was to vaccinate extensively until disease eradication, the second was to vaccinate only if the costs per incidence remained outside an acceptable level. The simulation demonstrated the impact of these two policies, and showed that the containment option leads to more cases, and costs, over a 20-year time horizon. Therefore, the model provided evidence to support the policy of eradication.

The next stage of the process involved the authors presenting their model and results at a stakeholder consultation, convened by the WHO Director-General Dr. Margaret Chan. The goal of this meeting was to consider the option of switching from eradication to control. Their author's system dynamics model, with its quantitative approach, long time horizon, and its analysis of the impact of wavering commitment, supported the case to continue the eradication policy, and this subsequently led to further resources to implement the eradication policy.

There are three modeling insights from this case study. First, it shows how system dynamics can be successfully applied to real-world problems, and achieve an impact in terms of policy analysis and implementation. Second, it demonstrates the importance of model purpose, where the modeling activity was focused on the core issue of whether to eradicate or control a disease. Third, the paper provides an excellent sense of the interdisciplinary skills required to build system dynamics models. The authors invested considerable time to understand the specific problem, and were well-positioned to defend their work to national and international policymakers, financial donors, fellow modelers, economists and epidemiologists. Furthermore, reflecting on Pidd's (1996) earlier definition of a model, it is evident that their system dynamics model has the following characteristics: