Published in final edited form as:

Syst Dyn Rev. 2018 ; 34(1-2): 327–353. doi:10.1002/sdr.1598.

SD Meets OR: A New Synergy to Address Policy Problems

Navid Ghaffarzadegan[1,*], **Richard C. Larson**[2]

[1]Virginia Tech, Department of Industrial and Systems Engineering

[2]Massachusetts Institute of Technology, Institute for Data, Systems, and Society

Abstract

We reflect on our past seven years of collaboration to develop systems models of U.S. higher education and scientific workforce development. Based on three recent modeling examples, we offer a methodological proposition that many traditional Operations Research (OR) models can be improved by including feedback processes as is commonly done in system dynamics (SD) modeling. Such models, even if simple and approximate, can be powerful, insightful, easy to communicate, and effective. While these modeling examples may not follow conventional SD or OR modeling, they benefit from and contribute to both schools of modeling. We argue that to build such synergy, modeling teams should be willing to create models building on the strengths of each school of modeling.

Keywords

system dynamics; operations research; feedback loop; queueing theory; policy modeling; science policy

1. Introduction

> "Out beyond the ideas of right and wrong there is a field. I will meet you there."
>
> Rumi (1207–1273)

Understanding complex social and policy challenges requires strong, rigorous, and innovative tools and techniques. Discipline-based research methods, however, all have their own advantages and limitations and, in some situations, strict adherence to any one method can unnecessarily restrict policy insights. The ultimate goal is to create and communicate policy insights and improve systems' behaviors successfully. A major step is accepting that "all models are wrong, but some are useful" (Box and Draper 1987, p. 424).

During the past seven years, the authors have collaborated to explore various problems related to the U.S. system of post-baccalaureate STEM education, U.S. science policy, and scientific workforce development (Ghaffarzadegan, Larson, Hawley, 2017). The authors

*correspondence to navidg@vt.edu, 703-538-8434.

[11]For an interesting article on this topic, see Rahmandad and Sterman's note, "System Dynamics or Agent-Based Models? Wrong question! Seek the right level of aggregation," at https://www.systemdynamics.org/assets/docs/sdorabm.pdf.

have different training backgrounds: system dynamics (SD) and operations research (OR). During our collaboration, a central methodological proposition emerged:

> Many traditional OR models can be improved to include feedback processes as is commonly done in SD modeling. Such models, even if simple and approximate, can be powerful, insightful, easy to communicate, and effective. To build synergy between SD and OR, teams should be willing to collaborate and combine critical elements of their practice.

Our paper for the 60th anniversary of system dynamics focuses on this proposition.

We first present three examples of our recent modeling work. The original models are published in various outlets (Larson et al., 2012, 2014, Ghaffarzadegan et al., 2015, Andalib et al., 2018); here the goal is to communicate common insights. Each model addresses a major science policy problem and benefits from both schools of modeling.

The first examines new grant awards as affected by total research budget. The model was developed to study the impacts of sudden changes in federal research grants. It is a difference-equation model informed by one major balancing feedback loop. The second depicts postdoc duration in the current U.S. science workforce, in which most postdocs will not secure tenure-track faculty positions and instead, discouraged, will leave postdoc status for non-academic positions. The third examines PhD population growth. Each model has major elements important in both SD and OR: feedback loops and mathematical representations of system physics.

2. Background

Operations Research.

Most historians date the birth of OR to the start of World War II. Two important leaders were both accomplished physicists: Patrick Blackett of the University of Manchester in the United Kingdom (for “Operational Research”) and Philip M. Morse of MIT in the United States (for “Operations Research”). They chose to allocate significant time during WWII to assume major leadership positions and apply their physical science approach to complex problems to help the war effort.[1] Both sides of the Atlantic enjoyed significant successes in applying the scientific approach of physics to operational and tactical problems of fighting the war. Examples include optimally locating radar stations in Britain to maximize the probability of detecting approaching enemy aircraft and the invention in the United States of optimal search theory, a heavily mathematical yet interdisciplinary methodology (classified “Top Secret” until the late 1950s) that was so valuable in locating and destroying enemy submarines in the North Atlantic.

After the war, OR approaches were brought to bear on commercial operations in areas such as logistics, manufacturing, inventory management, and scheduling. The field of OR had taken off!

[1] In 1948, Blackett was awarded the Nobel Prize in Physics for his investigation of cosmic rays.

The Operations Research Society of America (ORSA) was founded in 1952, followed one year later its sister organization, The Institute of Management Sciences (TIMS). Almost a half-century later, in 1995, these two major U.S. OR organizations merged to create INFORMS (INstitute For Operations Research and the Management Sciences).

In reflecting on the birth of OR, early ORSA and TIMS members realized that their mathematics, physics, and interdisciplinary approaches to problems had roots going far back in history – significantly earlier than 1940 or so. The field's approaches and techniques built upon early work in probability (1600s and 1700s), graph theory (Euler, 1736), queueing theory (A.K. Erlang, 1909–1915), Lanchester's Equations (F. W. Lanchester 1914), solutions to simultaneous linear equations (E. Stiemke 1915), facility location (E. Weiszfeld aka A. Vazsonyi 1936), and much more (Gass 2002). Many scholars contributed to the field by developing different tools and techniques of understanding and improving individual and organizational decision making such as Simon, von Neumann, Dantzig, and many others.[2] The tool kit was rich and growing. The field expanded over time, and today INFORMS publishes 15 different refereed journals, most being highly respected in their fields, and some do not emphasize mathematics or the physics approach (e.g., *Organization Science, Strategy Science*).

As one might expect, several sharply divergent views of OR emerged over the years. In the late 20th century, for instance, Russel L. Ackoff (University of Pennsylvania) argued that "the future of OR is past" – that OR had become "technique-dominated Operations Research." Ackoff had a point, in our opinion: the physicists of WWII cared not about techniques in the abstract, but rather cared about solving the problem (Ackoff and Sasinieni, 1968). If they used a tried-and-true technique, fine! If they had to invent new ones (e.g., theory of optimal search), then they did so. They were problem driven, whereas many OR PhDs who later became faculty members at research universities received accolades – including promotion and tenure – by publishing solely about techniques, usually not motivated by operations. This tension between technique-driven and problem-driven research persists, and it is not solely confined to OR.

If we examine the core of OR from the WWII physicists' point of view, we see both strengths and weaknesses. The strengths lie in the scientific method of physicists to solve short-term (operational) and medium-term (tactical) problems. Often lacking were longer-term responses to implemented changes, where the system or an adversary may adapt in response to decisions, thereby changing the parameters and possibly the physics of the system. Parameters of most OR models and methods are stated *a priori* and fixed for the duration of the analysis. This is where SD enters the picture.

Consider queueing, a field born in Copenhagen Denmark in the period 1909–1915. A.K. Erlang worked out sets of equations that predicted the performance of various Markovian queueing systems as a function of system load (expressed as λ), number of servers N, and the maximum available output flow rate of customers being served ($N\mu$). The parameters are assumed to be fixed and known, and the analysis assumes steady state, no transients. If the

[2]For an extensive list and information about profiles of major contributors to the field of OR see Gass and Assad (2011).

available service rate $N\mu$ were to decrease for some reason, no assumption was made regarding a concomitant adjustment downward in customer inflow λ. Parameters operated independently. A significant decrease in μ and/or increase in λ could cause the queue to grow without bound, implying that those seeking service would continue to do so even though the wait time tends toward infinity. Obviously, such models lack behavioral feedbacks.

A system dynamics modeler would include these behavioral feedbacks, as Forrester (1961) did in his first models. There would be feedback directly or indirectly connecting λ and μ. For instance, if arrival rate λ were to increase without a compensating increase in per-server service rate μ, then – over time --some factor viewed by the OR modeler as external to the queue system would act via the feedback loop to decrease λ (Barlas and Özgün 2018). Certainly in practice λ would not be allowed to reach a singularity. In real world terms, people considering joining the queue will balk, and those in the queue will leave ("renege"), if wait times become too large. Our favorite example is from Yogi Berra, the Hall of Fame catcher for the New York Yankees (1946–1963) and world-renowned for his "Yogi-isms." Asked about a popular restaurant, he famously replied, "Nobody goes there anymore. It's too crowded." In a sense, Yogi was the key element of a feedback loop: balancing the queue of customers!

System Dynamics.

Using concepts of systems and control theory, Jay W. Forrester developed SD in the late 1950s to model complexities of industrial and social systems. But Forrester's roots in systems and control theory date to the previous war decade, the 1940s. In 1940 – the same year MIT's Philip Morse created Operations Research in the United States, MIT's Servomechanism Laboratory was born to utilize control theory to create breakthrough hardware devices, also in response to the war effort.[3] Forrester, then a young graduate student, worked at the Servomechanism Laboratory, where he successfully directed a feedback control project to keep radars on ships aimed at the horizon – all in the presence of the ship's natural pitching and yawing (Dizikes 2015). His work complemented other efforts at the lab, including the stable aiming of ship-mounted anti-aircraft guns. Forrester was successful because he learned all the relevant theory, some of which was quite new – for example, Nyquist's (1932) stability criterion, negative feedback to ensure stability (Black 1934), Bode plots (1938),[4] and more. Control theory and these tools enabled system designers to utilize feedback to assure system stability, robustness, and limited or no oscillations.[5] We can see in Forrester's success with this theory the early attributes of what was later called System Dynamics.

[3]MIT Servomechanisms Laboratory, https://libraries.mit.edu/mithistory/research/labs/mit-servomechanisms-laboratory/

[4]Hendrik Wade Bode, https://en.wikipedia.org/wiki/Hendrik_Wade_Bode.

[5]In 1940, with the Tacoma Narrows Bridge in the State of Washington, the world witnessed an event in which uncontrolled positive feedback created accelerating resonant-frequency oscillations and destructive instability. Opened on July 1, 1940, the bridge (aka "Galloping Gertie"), with uncontrolled oscillations caused by local wind conditions and poor bridge design, collapsed into Puget Sound on November 7 of the same year. Surely this widely publicized event influenced not only future bridge designers, but also all of those (including Forrester) concerned with systems and their stable behavior. https://en.wikipedia.org/wiki/Tacoma_Narrows_Bridge_(1940))

Examining Forrester's early publications, such as *Industrial Dynamics, Urban Dynamics*, and *World Dynamics* (Forrester, 1961, 1969, 1971), we see that, like OR, SD was also a highly problem-oriented approach. Like OR, SD also evolved over time, addressing different topics including model validation, system archetypes, system maps, group model building, boundary objects, and behavioral analysis (e.g., Sterman 2000, Barlas 1996, Senge and Forrester 1980, Oliva 2003, Homer 2012, Senge 1990, Andersen and Richardson 1997, Andersen et al., 2007, Black 2013, Mojtahedzadeh et al., 2004). SD studies revealed cognitive barriers to understanding feedback loops and accumulation, supporting further the need to use simulation to communicate modeling insights (e.g., Sterman 1989, Cronin et al., 2009, Abdel-Hamid et al. 2014). Recently, there has been more emphasis on systematic use of textual data, and more systematic use of numerical measures, model calibration, and parameter estimation (Rahmanded et al., 2015; Hosseinichimeh et al., 2016; Kim and Andersen, 2012). Richardson (2011) claims that the foundation of the field is the "endogenous approach," having a broad model boundary to encompass environmental reactions that may lead to policy resistance and unintended consequences. Feedback loops, originating in control theory, are tools to represent such reactions.

Several strong and insightful mathematical models of social systems from the OR community have been consistent with the SD modeling approach – but the authors probably would not label their work as SD. For example, the famous Bass model of market adoption, which relies on two major feedback loops of word of mouth and market saturation, was developed in 1969 (Bass 1969), the same time *Urban Dynamics* was published. Other interesting examples include models of infectious diseases, some of which were developed by Kaplan and colleagues (e.g., Kaplan et al. 2002).

It could be argued that mathematical modeling of systems is what most SD and OR modelers have in common. We agree that the methods have not been completely separated and that occasionally over the past 60 years researchers from one field have shown interest in the other. Forrester was inducted into the International Federation of Operational Research Societies' Hall of Fame in 2006.[6] He is referred to as one of the pioneers and inventors of OR (Gass & Assad 2011) showing that SD and OR have not been as separated as it may be taught in universities. Furthermore, many SD papers have appeared in OR journals (e.g., Ford 1990; Paich & Sterman 1993; Anderson & Parker 2002; Joglekar & Ford 2005; Karanfil & Barlas 2008; Tebbens & Thompson 2009; Saleh et al. 2010), and various efforts have been made to compare conventional SD versus OR formulations (e.g., Barlas and Özgün 2018) or to use optimization techniques to enrich understanding of macro-level outcomes of SD models (e.g., Homer 1999, Vierhaus et al. 2017). However, many efforts seek to communicate a conventional SD model to the OR audience, or an OR model to an SD audience; too few seek integration of the methods.

Our central theme – the need for cross-pollination of OR and SD modeling approaches – can be illustrated in various problem contexts. Here, we select three examples from a complex social system of science policy and scientific workforce development.

[6] http://ifors.org/ifors-hall-of-fame/

3. Models

Since 2012, the authors of this paper have been supported by a research grant from the U.S. National Institutes of Health (NIH) to study science workforce development, both in biomedical fields and in social and behavioral sciences with applications to health. This project has been problem-focused, directly addressing NIH's concerns about science workforce development in the United States. Here, we review three illustrative models.

Model 1 – Magnified effects of research budget cuts

The first model addresses the dynamics of research funding as influenced by past funding commitments. Each year, the U.S. government allocates about $140 billion for the research activities of federal agencies such as the National Institutes of Health (NIH) and National Science Foundation (NSF), which in turn each year announce new grant funding opportunities, that typically generate several applications per grant awarded. Grants typically last for four years for the NIH and three years for the NSF. Federal agencies award multi-year grants to provide continuity to researchers, whose research programs often require multiple years to bear fruit. But federal funds are allocated to agencies separately for each fiscal year. Depending on the U.S. Congress, these allocations can increase or decrease from year to year. The complication is that prior commitments must be honored from the current fiscal year's allocation. Fulfilling prior commitments each year affects the funding available for proposed new research projects, just as the funding for new research will affect future commitments.

The key question is *what is the effect of a change in research budget on the ability to fund new research*? The question becomes most important during periods with changes in the budget, such as 1998–2003, when the NIH budget doubled, or periods when the potential exists for a government-level research budget cut. Figure 1 shows a simple causal loop diagram (CLD) as well as two simple equations from the model. The equations are for grants of four-years' duration. There are two simple balancing loops: Loop B1 represents fulfilling the past commitments; and Loop B2 is the major loop, in which increased annual budget leads to more new grants, more new grants result in more future commitments, and that in turn decreases funds for future new grants.

Let's first think about a simple example. Consider a federal agency that awards competitive research grants, each flat-funded for four successive years. Suppose in the past that the agency's annual budget for funding research activities had been $10 billion. In the steady state condition, 75% of each year's funding goes to commitments of the past three years ($7.5 billion) and 25% remains for new competing grants ($2.5 billion). Thus, when the agency announces four-year grants totaling $10 billion, roughly $2.5 billion is to be paid in the first year. The new grants, then, add to the next three years of commitments. Let us suppose that the U.S. Congress in year 2013 decides to reduce the next fiscal year's budget by 10%, which would decrease the total research budget to $9 billion. To fulfill the prior commitments totaling $7.5 billion, the new awards would have to decline to $1.5 billion, a 40% decline compared to the previous year, and four-times magnified in comparison to the 10% change in total funding. If the dollar size of the grants is kept constant, then the number of new grants declines by 40%. Assuming a constant number of grant applications, that means a 40% lower chance of getting funded, which has a significant impact on researchers – with potential negative career consequences for young scholars.

Let's generalize. Consider a federal agency whose flat-funded grants have duration τ years ($\tau = 4$ for NIH, 3 for NSF). The model has an insightful property: *For a federal agency operating in steady state with grant durations of τ, an abrupt X percent change in the agency's annual research budget causes up to an $X^*\tau$ percent change in new funding* ($X^*\tau \leq 100\%$). We call this the "Rule of τ." The main implication is magnified effects of changes in budget on new funding.

The impetus for this work was an NIH inquiry: Why, in the period 1998–2003 when the NIH budget was doubled, were there so many negative consequences of the doubling? Being careful to explain the Rule of Four (for NIH), we were able to illuminate the model's results satisfactorily to our NIH stakeholders. By examining the new funding available in each of the five years of growth and the following years of flat funding, we projected the entire NIH research community's reactions: "Early Euphoria" in 1998 and 1999, following by "Severe Hangover" in 2003 and beyond. Despite the fact that our analysis was conducted after the hangover occurred, our NIH colleagues were stunned that we accurately described the research community's unpublished reactions to the 1998–2003 doubling of research support using such a simple model – one they did not have prior to our analysis and one they now use to guide much of their thinking.

In the arcane world of federal operations, budget allocation is a much more complex procedure than depicted by our simple model. For example, not all of the NIH budget is allocated to external funding; there is always the potential of changing grant durations; some projects receive supplemental budgets to perform additional research; some get budget cuts based on their performance or for other reasons; and some projects have carryovers from past years. In the long run, more funding results in more PhD graduates and more funding applicants. We assume a discrete-time model, a practice not often suggested in SD, but was proper for this simple model since the Congressional budget is authorized annually.[7]

Reflection: The NIH budget model is a discrete-time difference-equation model built in an Excel sheet. It is a system dynamics model because it has a major feedback loop representing both the "physics" of grant commitments and the behavioral decision rule governing new grantmaking. Our choice of discrete time (versus the common SD modeling practice of continuous time, with the model solved by numerical integration) was due to the nature of the problem-in-hand.

[7]Although Congressional budgets are allocated annually, there are ongoing processes that happen during a year, especially at the research institution level, such as internal allocation of funding, writing papers, or writing grant proposals. Our model did not deal with such activities, and thus the assumption of $\Delta t=1$ was appropriate. In other cases, such as Gomez Diaz (2012), we had to model with much smaller Δt's to represent ongoing research activities and workforce training between two budget allocation events. Modelers should make sure that their results are not sensitive to Δt, but most importantly we would like to state that an SD model can be a time-discrete model – despite the general belief to the contrary. For an insightful discussion on the trade-offs between continuous versus discrete-event simulation in queueing models, see Barlas and Özgün (2018).

Model 2 – Postdoc Queue

Postdocs are early-career researchers with doctoral degrees employed in temporary positions, usually in universities, research centers, or government laboratories. Postdocs are paid significantly less than most other academics, and many see postdoc appointments as training opportunities and longer-term investments. Postdoc positions operate as "holding positions" for newly minted PhDs until they find tenure-track academic positions or decide to abandon the quest for an academic career.

Considering the importance of maintaining the flow of young scholars, two questions arise: *What is the average duration of an individual's postdoc "career"? What is the rate at which postdocs leave their postdoc positions for tenure-track faculty positions vs. non-tenure-track positions or industry jobs?* Given limited available data, answering these questions is not trivial. Estimating postdoc length by using available surveys is challenging, since most surveys gather data from PhDs currently employed in postdoc positions; it is unclear how much longer they will stay in such positions.

Data reveal that the majority of people who begin postdoc positions are interested in tenure-track academia, and they use postdoc positions as holding positions until finding their desired jobs (Hur et al. 2015; Grinstein and Treister, 2018). Of course, not everyone can find those jobs, since the supply of new tenure-track positions is lower than that demanded by new PhD's. From the OR perspective, the problem requires a basic queueing model: newly minted PhD holders join a line and wait for the service, that is, being assigned to an academic tenure-track position. But a major feedback loop exists and, like many other queues, this one also has reneging behavior, that is, some PhDs change their decision as they observe the lower-than-desired service rate and end up leaving the queue without being served.

Figure 2 shows a simple CLD representation of the model (left sides) and simple queueing model representation for the steady-state condition (right side). In Figure 2a, there is one major balancing loop (B2): *more postdocs → lower fraction landing Tenure Track (TT) positions → lower perception of fraction landing TT → higher fractional reneging rate higher postdoc reneging rate → fewer postdocs*. On the right side, we show the queueing formulation of the problem. In steady state, the problem can be simplified as the law of conservation of mass: the inflow to postdoc positions is equal to the total outflow consisting of two flows, those taking tenure-track positions and those leaving postdoc positions for non-tenure-track jobs. In a more dynamic context, the reneging rate can change and regulate postdoc population, similar to what the graph on the left side shows.

Consider a simple example. If every year about 17,000 new PhDs take postdoc positions, and about 3,000 of current postdocs take tenure-track positions, what should be the rate of reneging to keep the number of postdocs constant at 50,000? What is the average postdoc length in this steady-state condition? Two simple OR rules help here: 1) the law of conservation of mass indicates that to have a constant number of postdocs, reneging should be (17,000–3,000 =) 14,000 postdocs per year; 2) Little's Law indicates that average postdoc duration is 50,000/17,000 = 2.9 years. Simple math reveals that 18% of postdocs find tenure-track positions, and every year γ=14000/50000=28% of postdocs decide to leave and forget about a tenure-track position.

In a more general condition, the inflow and outflow change and reneging is affected by the chance of landing tenure-track positions. For this condition, the SD model can help further to estimate a more general condition in which fractional reneging rate (γ) is a function of the fraction landing tenure-track positions. In this formulation, γ will be endogenous.[8]

Figure 3 shows an estimation of the reneging rate and postdoc duration from the system dynamics model (solid line) in comparison to the similar estimations from the queueing model (dashed line). The estimations are close; the SD model shows slight changes over time. The SD model represents a behavioral mechanism for reneging and can also help us examine transition dynamics if the numbers of faculty positions or of PhD graduates suddenly change due to changes in funding.

Reflection: The novelty of this work lies in seeing postdocs as people waiting in a queue, and considering that long postdoc duration feeds back to people's decision to stay or leave the queue. In fact, any queueing model that includes reneging is inherently considering such a feedback loop, even if the model creators do not explicitly call it that (e.g., Kaplan 1988). In addition, as depicted in our SD model, the reneging rate is not necessarily a constant parameter, but can change in response to changes in different state variables in the system. The models that depict reneging as a dynamic response can explain non-stationary behaviors such as oscillation, and help us see the transition dynamics often missed in a steady state approach.[9] The use of the SD model in this problem was also novel. In contrast to the common use of SD models to simulate dynamic trends and predict different modes of behavior, here the problem was a value estimation problem: average postdoc duration and average reneging rate.

Model 3 – reproduction in academia, R_0

Our third model was developed to investigate PhD population growth in academia. We adopted R_0, the basic reproduction rate concept from demography and epidemiology. In academia, R_0 is the mean number of PhD students that a new tenure-track assistant professor will graduate over her/his entire academic career.

Here's a simple example: Consider all tenure-track positions in academia as one aggregate quantity. If there is a total of 20,000 faculty members, and that number has been constant for the past two decades, and assuming that each professor on average works for 20 years, then every year there are (20000/20) = 1000 new openings due to faculty attrition or retirement. Let's assume that each faculty member graduates only one new PhD during her/his entire career, and thus the number of PhD graduates per year will be (20,000*1/20=) 1000 new

[8]In the SD model, γ is a function of *perception of fraction landing TT*, r'. We use a simple linear function for this relation, $\gamma = a + b \cdot r'$; $0 \le \gamma \le 1$ and estimate the coefficients from model calibration: $a = 0.61$, $b = -3.38$. To formulate r', we use a simple smooth function with delay of one year (modelers' assumption): $r' = smooth(r, 1\ year)$ where $r = \mu/L$. In the SD model, the ratio of stock to total outflow is used as an approximation for time in postdoc.

[9]Many SD models of service or manufactory industries represent balking or reneging mechanisms when formulating negative effects of service delays on new incoming orders, and such formulations are common practice in SD. One example is Forrester's market growth model (1968); other examples can be found in Sterman (2000) and Oliva & Sterman (2010).

PhDs per year, which is equal to the faculty outflow rate. Put more simply, if every faculty member graduates only one PhD during her/his career, that one PhD will have access to a faculty position. But if each faculty member graduates more than 1, let's say 7.8 (the estimated number for engineering fields (Larson et al. 2014)), only 1 of the 7.8 will land tenure-track positions – that is, 13%.

The result can be generalized. If we consider R_0 as the average number of PhDs a faculty member graduates during her/his whole career, only one of them will be able to land a tenure-track position if that number remains constant. In other words, the chance of landing a tenure-track position is $1/R_0$. Although this is a simple calculation, the result have come as a surprise to many faculty members working for years in academia.

Figure 4 shows a simple CLD representation of the model. There are multiple loops, but let's stress one major reinforcing loop, more professors → more PhD graduation rate → more professors, and one major balancing loop, more professors → less gap (with desired number of professors) → less hiring → fewer professors. These two loops are similar to how the population of a country may increase for a while, eventually meeting a natural resource limitation ceiling.

Reflection: We did not simulate this model. However, the insights came from viewing PhD production as a reinforcing feedback loop limited by capacity (faculty positions). The main goal was very simple: to help improve our mental models so we could better address the question of PhD population growth in academia. One does not need software to describe or simulate the model; words and a little algebra are enough. From the OR perspective, we did not perform optimization in any form, nor did we prove a theorem. The original paper was well received and was covered by different media outlets, including the *New York Times* and *Discover* magazine. [10]

4. Approximate Simple Models with Feedback

Looking back at these models, we see major common themes across our efforts. While the models are small and simple, they communicate important insights. Consistent with basic principles in both OR and SD, we ensured that the models incorporate physical systems laws such as Little's Law and the law of conservation of mass. All variables in our models had operational, physical meaning (e.g., people, funding, time). Moreover, in contrast to many OR modeling practices, we questioned the assumption of constant or exogenously set parameters in the models and uncovered several phenomena feeding back to the physical systems.

In summary: (1) simple models can often provide big insights, and (2) linking SD with OR can provide significant benefits. The question now is whether we can develop practical guidelines for similar cross-disciplinary synergies.

It would be impractical to offer a step-by-step guide to building synergy between SD and OR. Such a guide will depend on the teams, technical background, problems of interests,

[10] For more information, please see Larson et al. (2014) and Ghaffarzadegan et al. (2015).

and more. But there are several points that can lead to higher likelihood of effective collaboration. In the following, we reflect on the process and then offer suggestions for both OR and SD communities that may lead to the desired synergies.

4.1 Model building as a learning process

A model is a depiction of some system phenomenon. The purpose — the problem to be solved — is essential in selecting the proper scope, size, level of aggregation, level of precision required and other model attributes. Many times, insights are developed during the process of model building, which may include various iterations of the same model with different levels of detail and precision (Randers 1980).

In the models described here our purpose was not to seek six-figure accuracy, but rather to find important insights about the system. A major goal in our collaborative work has been to inform managers, often by challenging their mental models and presumptions about their systems. An example is the "Rule of τ" in NIH annual funding, now accepted as the "physics of annual funding within the NIH." Developing the physics is very much in the spirit of Blackett and Morse, viewing OR as an approach to develop the physics of the systems in which we live and work.

Our second example involved queues. We typically think of a queue as a group of people standing in a line waiting to order hamburgers and fries, or obtaining cash from an ATM, or waiting to get through airport security. But the idea of a queue is much more general. With our broader concept of queues, it was only natural for us to think of the population of postdocs as a queue awaiting "service" in the form of appointment as a tenure-track assistant professor. But, unfortunately, the inflow to the queue far exceeds the service rate of the queue. That is, for most STEM tracks, the service rate desired by newly minted PhD's is significantly greater than the university system's offered service rate (number of new assistant professorships available per year). As a consequence, most STEM postdocs eventually leave the queue ("renege") without receiving their desired service. The causal physics of reneging, augmented with the feedback processes arising from the behavior of those in the queue, illustrate how traditional OR and SD models can be brought together in a synergistic union.

Sometimes, a modeler's best contribution is simply to introduce a simple but fundamental concept from an apparently totally unrelated field. Model 3, above, is an example: applying R_0 to academia. R_0 was conceived by demographers in Germany in the 1880s, defined then as the *mean number of girls a newly born baby girl would give birth to in her lifetime*. At that time, the number for Germany was about 1.06, suggesting slow population growth over generations.

Germany's R_0 today is about 0.75, suggesting – in the absence of immigration – declining population. Much later, the R_0 concept was adopted by epidemiologists, who redefined it as the *mean number of secondary infections produced by a typical infected individual circulating in a population of people who are all susceptible to becoming infected*. A typical value for R_0 with seasonal influenza is 1.4; for measles (assuming no inoculations), it is between 12 and 18. The idea – generation-to-generation growth or decline in a population – is the same.

So it was natural for us to apply R_0 to generation-to-generation growth of PhDs, noting the "birth rate" of professors in giving birth to PhDs. The results proved to be unexpectedly enlightening for many, not only in the NIH but also in universities – where the thought of introducing "professorial birth control" had never been discussed. Yet, in many STEM fields, the unintended negative consequences of so many PhDs are becoming apparent. Introducing R_0 in this domain, we believe, is altering the thought processes of many who support doctoral research and worry about the careers of those with STEM PhDs.

Finally, we think it is important to consider that these models emerge through a long-term process of modeling. At least 10 different models, including the three presented here, were developed during this project. In all cases, we developed different iterations of the models, some of which were complicated. Mauricio Gomez Diaz, then a master's student in MIT's Engineering Systems Division, built a more comprehensive system dynamics model of unintended effects of change in federal funding for his thesis, supervised by the authors of this article. Mauricio's model, which included more than 100 equations, was tested against various datasets and was presented in the system dynamics society conference (Gomez Diaz 2012). Later, Yi Xue, Maryam Andalib, and several other students joined the project, each studying new aspects of science workforce development and taking steps forward. There might be a systematic pattern here. It appears that many times, models work as learning tools for exploration, help communication, bring insights, and give birth to new ideas and new models. In the evolutionary process of model building, parent models pass on some central "genes" to new models, and the process continues until they eventually lead to the "fittest" models. As simple approximate models are more effective communication tools, they have greater chances of spread and survival.

4.2. Notes for OR modelers: What's inside and outside

OR models, with their pre-stated fixed parameter values, often treat factors that might influence and change those values as "outside of scope," that is, exogenous to the models. SD modelers, who are more comfortable with causal loop diagrams and inclusion of factors that are important but not so easily measured with precision, tend toward models with broader boundaries that treat more phenomena as endogenous to their models. So, we might say, *what is exogenous to the OR model is often endogenous to the SD model*. This realization presents the major synergy linking the two approaches.

We illustrate our proposed linkage through queueing models, using the queue metaphor as one easy illustration. Queue models are at OR's core, where there is only one equation with the standing of Newton's $F=ma$ in physics – "Little's Law":

$$L = \lambda W .$$

Here, the queue is assumed to be in steady state ("equilibrium"), and the definitions are as follows:

L = time-average number of customers in the system, both in queue and in service.

λ = the rate at which customers enter the system.

W = mean time a random customer spends in the system, both in queue and in service.

MIT Professor John D.C. Little derived this law in the 1950s while working as a PhD student under the supervision of OR co-founder Philip M. Morse. Little was Morse's first OR PhD student and most likely the first OR PhD student in the United States. Little's Law is remarkable in that it applies to every sort of steady-state queue regardless of the microstructures of the arrival process, service process, or even the balking and reneging processes. As the reader has seen, we applied Little's Law to postdoc queues.

In another paper (Larson and Gomez Diaz, 2012), we applied Little's Law to university professors, where

L = time-average number of tenure-track faculty members at the university.

λ = the annual rate at which new assistant professorships are awarded.

W = mean number of years a random faculty member remains at the university (the "mean faculty career duration").

In this application, we had data on L and empirical probabilities that allowed us to estimate W for two conditions: mandatory retirement at age 65 (once U.S. federal law) or no mandatory retirement age (current federal law: no "age discrimination"). In solving for two different values for λ, one for each case, and keeping the total number L of tenure-track faculty members fixed, we found that lack of mandatory retirements at age 65 reduced the in-flow of new assistant professor positions by about 19%. In a sense, one could argue that the reason λ declined was to keep L at the desired level (a balancing feedback loop: more L $\rightarrow$ less need to hire $\rightarrow$ less λ $\rightarrow$ less L). The MIT dean of Engineering was quite surprised and very interested in these results. Again, we see the power of simple approximate models.

Based on these examples, we believe there are potential new synergies between SD and OR the endogenous-exogenous paradigm. Let's take a simple queueing model with continuous inputs at rate λ, output at rate $\mu \leq \lambda$, and dropout at rate $(\lambda - \mu)$. As Figure 5 shows, a stock-flow model can represent the queue consistent with the law of conservation of mass and how queues are studied in OR.

The idea in Figure 5 is not necessarily new to OR. State-dependent balking and delay-dependent reneging are human acts of rejecting or abandoning the queue based on feedback from its current state, an idea central in system dynamics (Forrester 1961) and recognized by some OR scholars (Udagawa & Nakamura 1957, Haight 1957, Ancker & Gafarian 1963). However, many OR models assume the parameters governing reneging and balking are fixed and independent of changes in customer arrival, service rates, or expected wait time. That is, most OR "balking and reneging" models assume customers balk or renege with pre-stated probabilities.

However, thinking about long-term dynamics, one might argue that the Figure 5 model does not sufficiently represent how new customers may react to the state variable, queue length, or how reneging may change as service rate declines. In fact, the entrance rate and reneging rate, in the long run, can react to the system status, and one needs to include them as part of a feedback loop structure (Barlas and Özgün 2018). The result is a queueing system with feedbacks not contained in the fixed parameter OR model; Figure 6 shows the idea. This development results in a feedback representation of reneging (loops B1 and B2) and balking (loop B3), two behavioral phenomena that are observable in long queues, as well as queue's physical capacity which can limit admission to the queue (loop B4). As we see, these feedbacks go beyond simple first-order state-dependent OR formulations, and commonly assumed fixed parameters are treated as endogenous variables.

And this is not the end. There are also context-specific feedback loops that could be added. Consider how long lines of cars waiting at a gas station can signal to the public about potential resource scarcity. A long queue in that example suggests low levels of the resource and may encourage more people to join the line, forming a reinforcing loop. Another example concerns the enterprise-level reaction to the queue: as the queue length increases, employees may work harder, or the service enterprise may employ better technologies, or it may hire more people to increase its service rate. These loops are depicted in Figure 6 (loops R2 and B5).

These phenomena, of course, do not happen in all contexts and they are not the only feedback loops that can be added to the model, but they can be important in improving a queueing model to more accurately describe a system phenomenon, and to bring new insights to improve people's mental models. Think of our Yogi Berra example. Initially his New York Yankee teammates would arrive at the restaurant and, observing the queue, either join it or balk. If they join, they may renege if the wait becomes too long. All of this, in the short and medium term, can be modeled by fixed parameters for arrival rates, service rates, and balking and reneging probabilities. But, as the restaurant becomes more popular over time, meaning an increase in arrival rate λ, the Yankees experience ever more congestion, being increasingly discouraged by their need to balk or renege or to stand in line for ever greater durations. Eventually, they may subtract themselves out of the pool of customers who frequent the restaurant, decrementing the new larger λ accordingly. Their exiting behavior is a type of "market correction." Later as the number of customers decrease, and potential customers learn about it, new people may arrive to enjoy quicker service, which can lead to fluctuations in the number of customers. Including these feedback loops, including the nonlinearities and delays in them, may lead to dynamics quite different from those arising in models with fixed balking and reneging parameters as modeled in OR.

In sum, modelers can benefit from considering feedback loops driven by factors viewed as external to the OR model but internal to the SD model. Feedback loops can arise from behavioral responses in the system, or can come from cycles of material flow (behavioral feedback versus material feedback/flow). While the latter is often considered in OR models, system complexity usually arises from behavioral feedbacks. These factors are important in practice but are often ignored in traditional OR modeling.

4.3. Notes for SD modelers: question the “norms” of the practice

Building trust in SD models and in communication with non-SD collaborators requires avoiding some misconceptions commonly held by many novice SD modelers. We suspect some of these misconceptions are widespread enough that they are seen by some as central to the method. Therefore, it is important to recognize their problematic nature explicitly and avoid reinforcing them in SD modeling and in the language we use to communicate our work. Here we offer six salient examples of these misconceptions.

Misconception 1: SD is about deterministic differential equation modeling.— We believe this is incorrect technically and inaccurate historically. Stochastic elements are central to many system dynamics models, including the very first SD model, Forrester’s supply chain model (Forrester 1961), and a host of others including macro-economic models with long and short-term economic cycles (Forrester 1982), models of path dependency where effects of initial incidents or decisions can determine the future path (e.g., Sterman 2000, Sterman & Wittenberg 1999), and expert decision making models where random poor outcomes can inhibit learning from feedback (Ghaffarzadegan 2011). It is important to note that in all SD models, the endogenous thinking and the recognition of behavioral conceptions of decision making are foundational.

One can remain true to these foundations using different mathematical representations. Deterministic differential equations are one, but SD models can also use a variety of other computational architectures, including difference equations, stochastic differential equations, or discrete event and agent-based models, among others, as long as they incorporate endogenous perspective. Our models 1 and 3 in this paper are examples of SD models not formulated as differential equations.

Misconception 2: SD is about aggregate modeling.—Aggregation is a matter of perspective. A model representing individual universities may be seen as disaggregate in the study of a national-level education system, and aggregate in understanding decision making within universities. More broadly, while aggregation often helps with simplifying models, the choice of level of aggregation is determined by a model’s purpose (Rahmandad & Sterman 2008). Whether we should model a phenomenon in aggregate (e.g., population level) or at the individual level is a question of unit of analysis, and depends on the problem. An SD model can be developed at an individual level to depict major feedback loops that one person faces during the time period of analysis (e.g., Hosseinichimeh et al. 2015, Lamberson 2016). Thus, what is often referred as an agent-based model, if it respects system physics and includes feedbacks, is a system dynamics model with an agent as the unit of analysis.[11]

Misconception 3: SD is about Vensim or Stella or Powersim or …—SD is not defined by use of any particular software platform, coding language, or other implementation feature. While traditional SD software packages such as Vensim, Stella, Powersim, or Anylogic have been employed in many SD research projects, one can use a variety of other platforms to implement an SD model. A system dynamics model can even be built in Excel (as we showed with Model 1 above). Moreover, one can build, in any of these software packages, models that do not qualify as SD models because they lack appropriate representations of system physics, feedbacks, or the behavioral decision processes of the actors in the system.

Misconception 4: More feedback loops make better models.—While the endogenous perspective is at the heart of SD, more is not always better. It is important to state that we agree with Forrester that lack of data is not a proper excuse to omit important feedbacks, but we believe the cost of vigorously adding feedback loops is often underestimated. When the goal is insight generation, the marginal benefits of adding feedback loops decline as the model gets more and more detailed. More interconnected maps may generate more questions and doubts than answers and insights. Many of us, when presenting a detailed model, often face this question: *How did you find a value for that specific parameter*? It arises from the audience pointing to an inconsequential parameter in the model for which quantitative data did not exist, and it is where your audience became distracted and was no longer following your main points. We argue that the focus should be on identifying the dominant mechanisms in the model and providing various types of evidence to support those mechanisms, while leaving out detail that may distract. To clarify we are not against testing a wide range of dynamic hypotheses, but we are against “spaghetti-and-meatballs” models, i.e., a detailed interconnected map of variables where the only insight is that they are highly interconnected.

Misconception 5: Building a small model is easier than building a detailed model.—Modeling is a process, and any model might go through different phases of expansion and contraction (Randers 1980). Our experience is that modeling can begin from simple models, be expanded as the modeler explores the various aspects of a problem, and eventually be reduced to distill the major mechanisms. Often, the first small models are inadequate, and a team of modelers converges on a good small model after significant exploration of the problem through cycles of expansion and contraction. Thus, small models are not necessarily only the early concept models, as some see them; they can be the more advanced distillation of insights emerging from detailed, complicated models that can only be built towards the end of modeling engagement. It’s just like the oft-used phrase attributed to French mathematician and philosopher Blaise Pascal: “If I had more time, I would have written a shorter letter.”

Misconception 6: Cross-disciplinary modeling is about making SD models understandable to other disciplines.—We acknowledge that making outcomes of SD modeling projects more understandable to other modeling communities, as described in Repenning (2003), is important and fruitful. However, we argue that cross-disciplinary modeling is much more complex than communicating final outcomes. It is about the entire process from the start to the end. It is about learning, in both directions. Thus modelers need to be open to techniques and insights from other methods. If you hope to learn from and influence others you must build your work upon the relevant work in the disciplines you hope to engage in dialogue. Doing so requires spending significant time reading related material, understanding the language of different disciplines, interacting with scholars and practitioners in other disciplines and domains, and, most importantly, engaging any inquiry with the mindset that there are significant lessons to be learned from other disciplines.

Each of these misconceptions is a pitfall. By avoiding them, SD modelers are more likely to create synergy with modelers of other disciplines.

5. Closing Remarks

In this paper, we have been compelled to reach across traditional academic boundaries – often necessary when one takes a problem-oriented approach. We have argued in favor of a synergistic link between SD and OR. Both methods were born of necessity in World War II, and each has provided decision makers with important insights.

While we encourage finding areas of synergy between SD and OR, we also acknowledge the significant benefits and impact of past studies specific to one or the other of these disciplines. Past studies and models have informed our practice, and not only those from SD and OR; we already mentioned the impact on our third model of German demographers from a century ago.

We also stress that "small" does not mean "easy" or "incomplete," and building small models can be much more difficult than building large-scale, detailed models. Modelers with a synergistic mind set can start with simple models that are compatible with both traditional OR and SD approaches. Then over time, as the physics of market and behavioral corrections become known via observation and data, feedback loops can be added to explain and model the corrections. In this dynamic process of modeling, modelers learn about the system as they build and test the models. Often, powerful small models come after refining, testing, and improving detailed large models. Many times, small models are the natural consequence of simplification of well-tested larger scale models. Small models aid communication (Repenning, 2003; Ghaffarzadegan et al., 2011). The ongoing process of modeling, simplification, and communication is essential in breaking down disciplinary silos, leading to interdisciplinary work (Larson 2016), such as that which we offer here: a bridge between SD and OR.

The big distinction between traditional OR models and SD models is that OR models are typically "open loop" with respect to parameter values. In most queueing, linear programming, or graph-oriented models, factors treated as constants (parameters) actually vary over a longer time horizon, and vary as the endogenous consequence of feedbacks in the system under study. Integrating OR concepts and tools with the endogenous perspective of SD offers potentially large synergies.

Our dream is to modify many traditional OR models with SD feedback loops driven by forces outside of the traditional OR modeler's universe. Not only λ and μ of queueing, but the parameters of a linear program, the weights of the arcs and nodes in a graph, the parameters of a decision tree, and more could be affected by factors commonly treated as exogenous in the OR modeler's world but that SD modelers see as endogenous. The result would be an exciting new set of models that yield new insights.

Acknowledgments

The National Institute of General Medical Sciences and the Office of Behavioral and Social Sciences Research of the National Institutes of Health (NIH) supported this work (Grant 2U01GM094141–05). We especially thank Mauricio Gomez Diaz (MIT), Yi Xue (MIT), Maryam Andalib (Virginia Tech), and Joshua Hawley (Ohio State University) for their assistance in developing the models described and in data gathering. We thank Hazhir Rahmandad (MIT) for helpful comments on an earlier draft. The authors benefited greatly from the encouragement and supportive suggestions of John Sterman, Nelson Repenning, and anonymous referees; we thank them with heartfelt sincerity.

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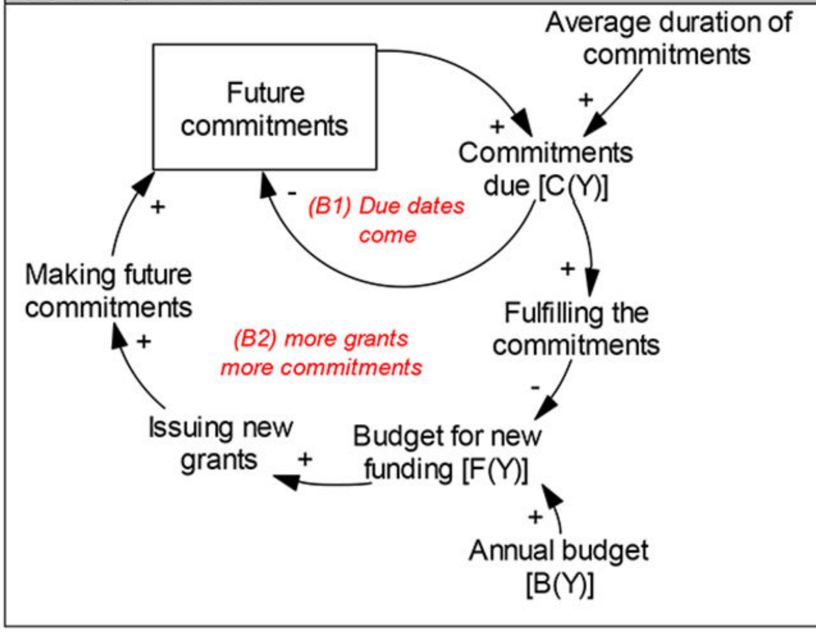
(a) Simplified CLD



(b) Mathematical representation

F(Y) = B(Y) – C(Y)
C(Y) = F(Y-1)+F(Y-2)+F(Y-3)

B(Y): Budget for research in year Y
F(Y): Funding available in year Y for new research grants
C(Y): Commitments due in year Y

Figure 1:
Modeling multi-year grant funding as affected by past commitments: (a) a simple causal loop diagram; and (b) a simple mathematical representation of 4-year grants

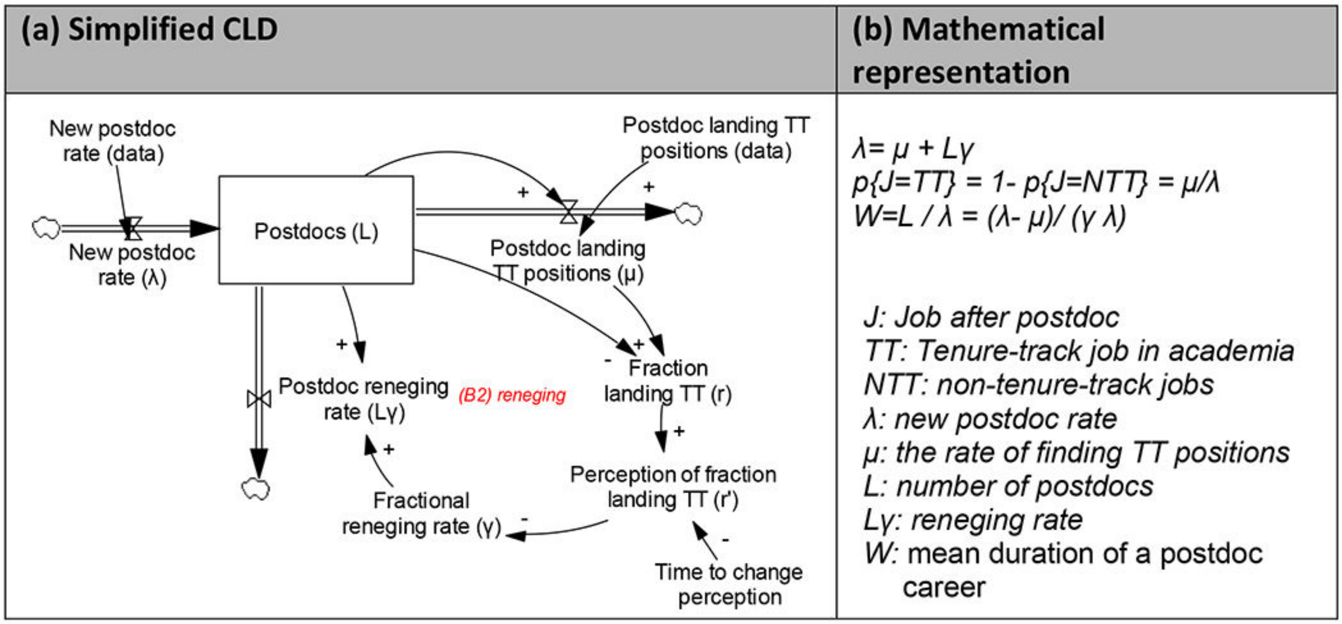


Figure 2:
Modeling postdoc queue as a function of entrance and postdoc duration to estimate postdoc length and reneging rate: (a): a simple causal loop diagram; and (b) a simple mathematical representation of postdoc queue in steady state

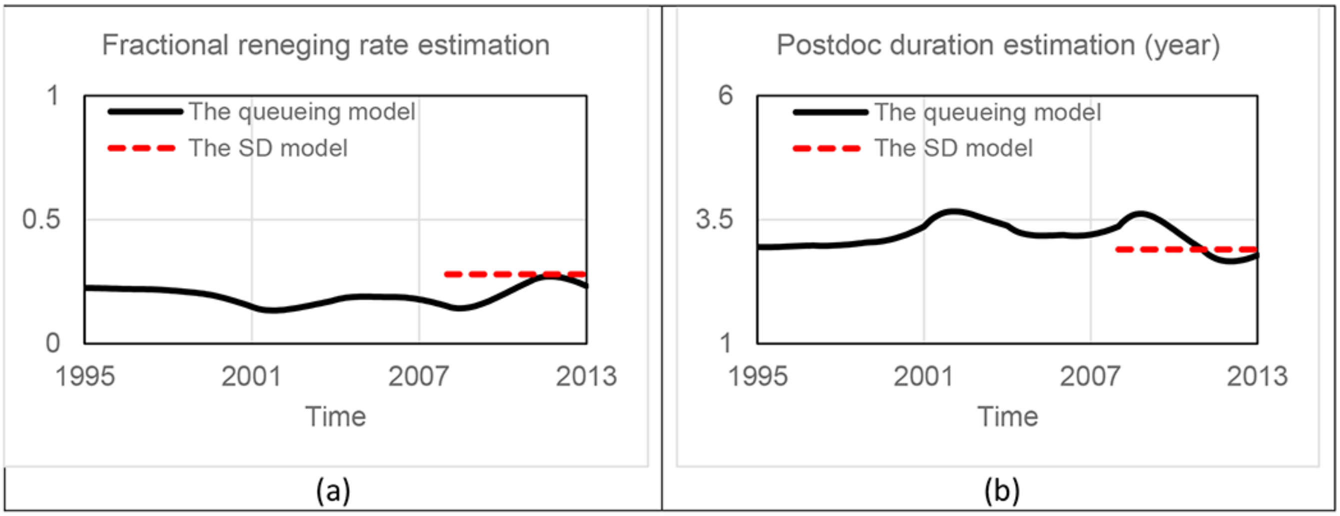


Figure 3.
Estimation of reneging rate (γ) and postdoc duration (W) from the SD model (solid line) and comparison with the queueing model in the steady state (dashed line).

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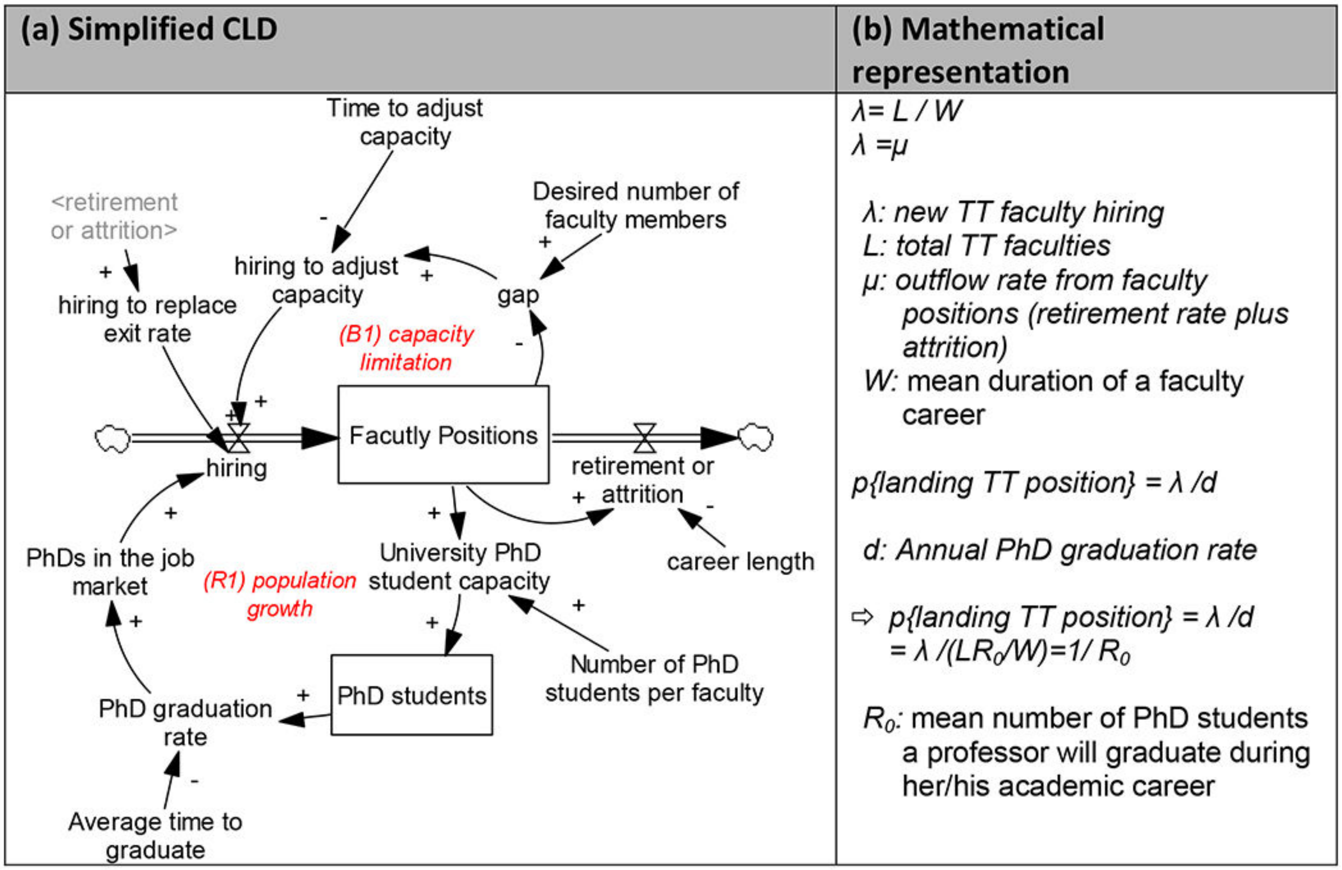

Figure 4:

Modeling PhD population growth: (a) a simple causal loop diagram; and (b) a simple mathematical representation in steady state. Note: a formal model may depict how PhDs are admitted and graduated in universities; here we show a simple representation.

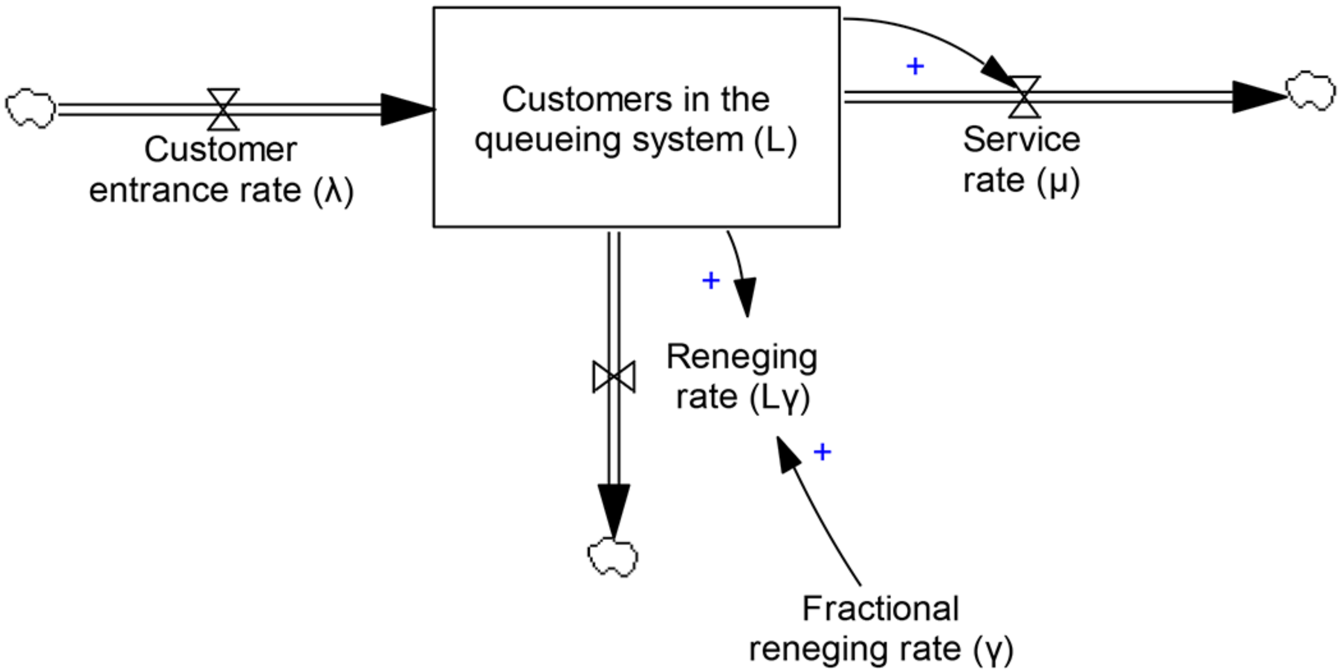

Figure 5.
A stock-flow representation of a generic model of a queue, with queue length being the state variable.

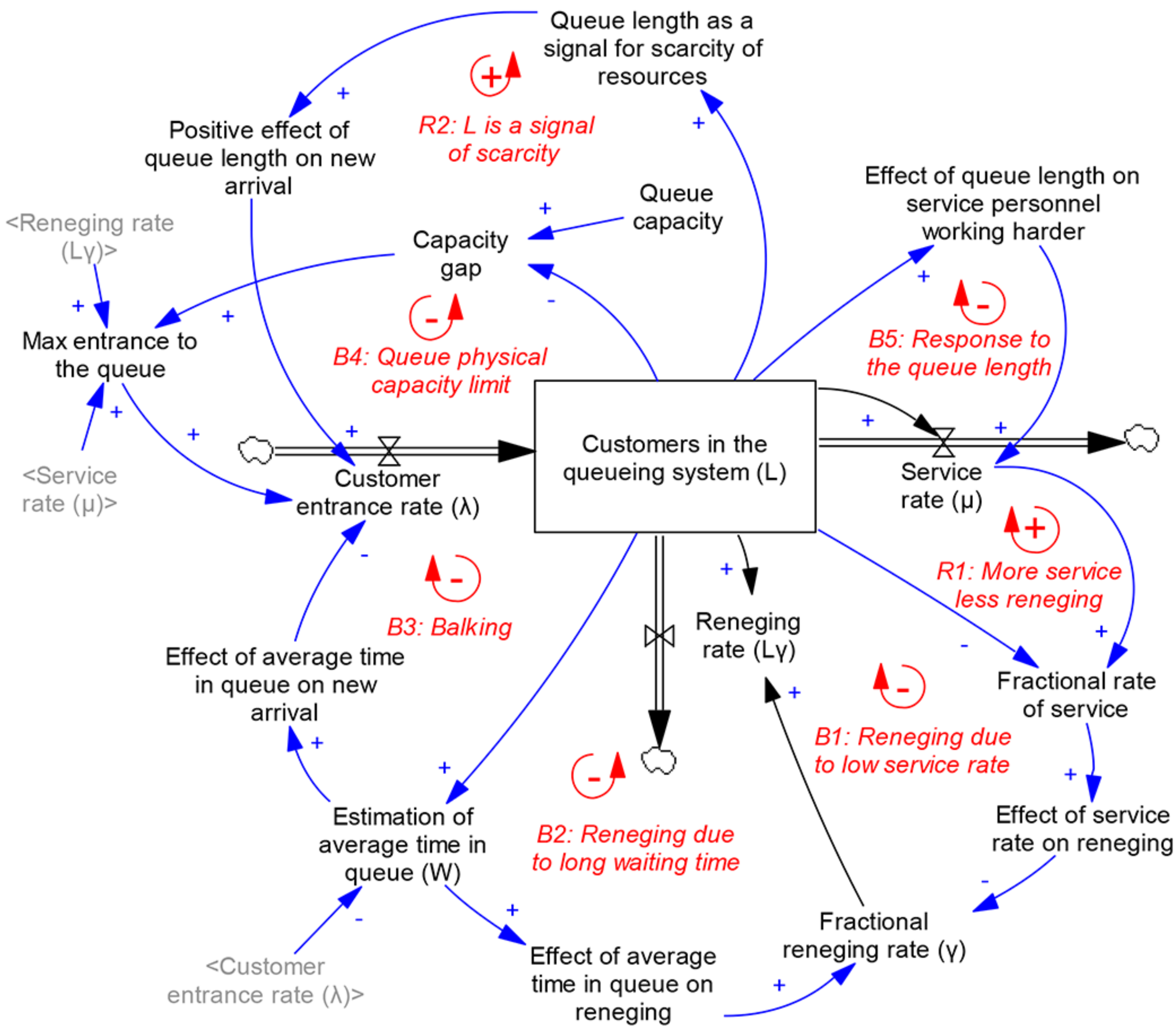

Figure 6.
A more developed model of a queue, using the dynamic queue model to explore contextual theories.