Learning from System Dynamics Simulations:
Time Compression in System Dynamics
versus
Time Dilation in Power System Simulators

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Abstract

Highly complex mathematical models have been used to simulate the stability of the electric power system. After years of development, however, even the best of these models can fail to simulate the conditions leading to major blackouts. The models are further challenged by changes in regulatory rules and increased wind generation. The industry needs improved mathematical methods, and the findings from system dynamics work on simulators might be useful in shaping the methodological research.

The paper summarizes the use of system dynamics simulators for learning. It then describes differences between these simulators and the simulators used in power system training. Subjects in system dynamics studies have limited time for experimentation and reflection, especially when compared to the time for subjects in the power industry. Another important difference involves time compression versus time dilation. Time is compressed in system dynamics simulators, but time unfolds in slow motion in power system simulators. In other words, power system training is based on *time dilation* rather than *time compression*. We explain how these and other differences limit the transferability of system dynamics findings to the power industry.

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1. Introduction

Our research is part of an investigation into mathematical methods in the electric power industry. System dynamics has been used to great advantage in strategic planning in the power industry (Ford, 1997, 2008); we ask whether it would also be helpful in developing better methods to simulate short-term dynamics, including decision-making by power system operators.

At the operations level, the industry faces unique challenges in meeting the demand for power in an instantaneous fashion across a complex grid. Complex models have been used to simulate the vulnerability of the system to loss of control. But these models can fail to show the most dangerous instabilities that can lead to regional blackouts (Kosterev, 1999). Some argue that the models are out of date due to major changes the regulatory rules. Others stress the challenges of integrating increased generation from wind and solar, resources that cannot be scheduled in the same fashion as fossil-fueled power plants. We look to system dynamics simulation for insights on improved methods for power industry modeling.

System dynamics simulators, board games and computer assisted games act to compress time. A familiar example is the product distribution board game. The inventory dynamics that unfold over 50 weeks in the real world are recreated in 50 minutes in the board game. Time compression is valued since most investigators are interested in long-term dynamics. Also, many investigators are limited by the time constraints of class meetings or executive workshops.

Training simulators in the power industry are quite different (Smith 1985). The trainees invest much more time in training, both in preparation and in simulation. When they do interact with the simulator, dynamics that occur in seconds on the power grid may appear in minutes in the simulation. Viewing the simulator is like viewing the slow motion replay on television. With slow motion, the viewer sees with clarity. And with enough exposure to slow motion images, trainees learn to see with more clarity and react more effectively in real time. In short, the power industry looks to simulations for *time dilation* rather than *time compression*.

We turn now to the experience of system dynamics researchers in the development of methods to measure subjects' learning with model-based simulators or in model-based board games. Supporting information is provided in two appendices:

- Appendix A describes system dynamics learning in a board-game simulation of oscillations in a product distribution system. The game (often called *the beer game*) is widely used in system dynamics education. The tendency for the subjects' ordering behavior to create and amplify the oscillations is potentially relevant to our research on the power industry.

- Appendix B describes a system dynamics model of pumped storage operation. The pumps and generators are used to compensate for scheduling errors in wind generation in the Pacific Northwest. The model illustrates the potential of system dynamics to simulate short-term operations of a narrowly defined portion of the power system.

2. Measuring Learning from System Dynamics Simulators

Tables 1 and 2 provide comments on studies reviewed for their approach to measuring learning. This is a small subset of the many papers on the measurement of learning. But we believe the sample is sufficient to support our conclusions on the transferability of key concepts from system dynamics to the challenges of operator training in the power industry. The studies deal with widely varying systems, ranging from control of supply chains to control of wildlife populations. They differ widely in the protocols for student experimentation, scoring of behavior, debriefing and measurement of learning. Our review does not reveal a clear clustering, so we list the studies in alphabetical order.

Alessi 2000	describes the need for user friendly/educational interfaces and a method to integrate the use of Stella and Authorware, a method to boost the interface capabilities.
Anderson et al. 1997	presents interesting insights into measured learning research design; methods include case studies, surveys and experiments; deals with both measurement problems and practical problems.
Anderson & Morrice 2000	describes using the *Mortgage Service Game* to enhance understanding of supply chains that operate without finished goods inventory; participants learned from their own results and the results of others.
Bakken et al. 1992	describes learning laboratories and the impacts of feedbacks on decisions; the labs provide opportunity for reflection and experimentation and they increase the ability of subjects to transfer ideas to other systems.
Baaken et al. 2006	describes changes in perception of success and effectiveness when a modeling intervention guided subjects to explore the network structure within a classical hierarchical organizational structure.
Borštnar et al. 2007	discusses the influence of information feedback on decision processes; found that individual feedback via simulation results improved decision making; group feedback contributes even more significantly to improved decision making.
Cavaleri & Sterman 1997	describes some of the challenges of collecting data about learning when in a real modeling intervention that strives to enable systems thinking.
Christensen et al. 2000	describes how to use causal loop diagramming as a way to assess learning through an analysis of the comprehension of complexity.
Dogan & Sterman 2006	provides a statistical explanation of seemingly extreme and irrational ordering patterns by some subjects in the beer game; the behavior of these "outliers" is viewed as an attempt at early hoarding.
Doyle et al. 1998	describes a methodology for using mental map coding for measuring subtle changes in mental models due to an intervention; researchers believe the method seems to be capturing a transitional state as subjects move from novices toward a level of somewhat more expertise.
Dutt & Gonzalez 2007	describes a model of decision making based on real data of subject's responses to a linear system that was either growing or declining; subjects were better at assessing and responding to a positive slope versus a negative slope; subjects took more time to assess positive slopes than negative slopes. (also, see Gonzalez & Dutt 2007)

Table 1. System dynamics papers with comments on measuring learning.

Grossler et al. 2000	describes testing the influence of model transparency (access to feedback structure) in business simulation; game results did not correlate with knowledge tests. The groups that received information about the system's structure by presentation performed significantly better in games; there was little transfer of knowledge from gaming exercise to post test; however, time was a limiting factor in learning and in this case was restricted due to the experimental design.
Howie et al. 2000	describes experiments with subjects operating Strategem-2, a management decision-making *microworld*; the control group operated the original *microworld*, and a test group operated the same model with a new interface; comparison found that improved interface can reduce the subjects' misperception of feedback
Huz et al 1997	describes an evaluation to capture shifts in thinking, while reminding us that many projects are designed to measure short term learning, not long term learning
Jensen 2003	noted that participants used an action sequence (rather that a mental model of the system); subjects' discovery of a good action sequence does not constitute genuine learning about the underlying cause of the problematical behavior
Langley & Morecroft 1996	describes the importance of learners to transfer concepts to other systems; explains that group feedback on simulations improves learning.
Martin et al. 2004	describes multiple iterations of the beer game in which subjects with extended practice achieved better control of inventory oscillations.
Plate 2010	describes *Cognitive Mapping Assessment of Systems Thinking* as a way to assess causal maps created by middle school students.
Rahmandad et al. 2009	modeled learning through the design of a simulation model that tested four types of information integration to study the effect of delays; examined the assumption that learning could be measured by convergence to an optimum.
Schaffernicht 2009	describes the use of causal mapping to explore learning; matrices and maps were used to evaluate all of the causal relationships brought up by the subjects.
Skaza & Stave 2009	examines the students' ability to recognize interconnections, to understand the difference between stocks and flows and to understand the process of accumulation; builds from previous work by Hopper and Stave (2008)
Spector et al 2001	investigates black box learning environments and found marginal learning, as measured by causal mapping.
Stave et al 2011	describes the history of using system dynamics models in an environmental science curriculum; describes the process of assessment used to determine if students were better able to understand environmental science.
Sterman 2000	provides a careful explanation of subjects behavior in the production distribution game (the beer game); documents the subjects failure to account for around two-thirds of the product in the 'supply line" when making ordering decisions
Sterman & Sweeny 2002; Sweeney et al 2000	describes subjects' responses to integrate the effect of flows over time; their responses reveal inability to perceive how slowly some stocks adjust to changes in the flows; sheds light on the public's misperception of the importance of public policies to start early to move stocks in a better direction (i.e. carbon policy)
Tabacaru et al. 2009	emphasized the need for learning through experience and extended practice and tested four aspects of recognition (i.e. cues and non-salient factors, causal relations, goals, and decisions).

Table 2. More system dynamics papers with comments on measuring learning.

3. Measuring Learning

The studies reviewed here include a variety of methods to measure learning. Many studies attest to increased learning, but there are a significant number which report that little learning took place. This is a surprising result given that most report an increased enthusiasm when subjects are allowed to experiment with system dynamics models and games.

Conclusions about little learning beg the question of what we expect the subjects to learn. In some studies, investigators expect the subjects to arrive at deep insights about emergent behavior. This is an ambitious goal, but perhaps a natural goal since many papers attest to the power of system dynamics to help individuals and organizations arrive at deep insight. Unfortunately, many system dynamics interventions are limited by the academic environment where classroom time leaves subjects with limited time for preparation, analysis, participation and reflection. Given the short time frame of many interventions, should we realistically expect subjects to acquire deep insights?

The researchers face difficult challenges as well. For example, just how does one measure the acquisition of deep insight? Similarly, how do investigators measure a change in intuitive or reactive capacity that becomes expressed at a time and situation well beyond the original intervention? Perhaps the subjects' capacity for deep insights about emergent behavior is similar to other learned behaviors --- it is a product of experience, application and reflection over time. These thoughts lead us to be cautious about claims that computer-based games lack the ability to build deep insight about dynamic behavior.

We view computer-based games as promising, but their application should be accompanied by continued research on measuring what the subjects are learning. Rather than setting our sights on the measurement of deep insight, we may do better to measure learning that is more within the grasp of the students with limited exposure to our ideas and our interventions. Skaza and Stave (2009) give useful examples of what we might measure. They examine environmental science students' ability to recognize interconnections, to understand the difference between stocks and flows and to understand the process of accumulation.

This paper focuses our attention on the measures of learning. Our review reveals that system dynamics studies rely on one or more of the following measurement methods:

1. simulation performance (scores in playing the game)
2. surveys or written tests,
3. comparison to expert performance,
4. qualitative analysis and individual reflection, and
5. transferability to other contexts.

3.1 Simulation Performance

An encouraging aspect of computer based games is frequent requests from students to play again. We often hear the students asking to stay late and try again:

Just give us one more chance to play the game.
We can do better next time.

Their enthusiasm and competitive spirit are admirable. Many games include a score keeping calculation to encourage competition. So it is natural that investigators turn to the students' scores as a simple, clear indicator of learning.

Measuring student scores may reveal the ability of students to play the game many times and memorize the sequence of decisions that delivered the scores. But such students are subject to the *video game syndrome* --- playing the game over and over with the goal of memorizing an action sequence. It's important for educators to guard against video game behavior by calling on students to explain their thinking (not just the action sequence). In the parlance of system dynamics, we should ask students to explain their *policy*, not their *decisions* (Forrester 1961). It is also helpful for instructors to change the external conditions or the model's internal structure before the students replay the game. The changed conditions will help subjects appreciate the difference between memorizing a sequence of decisions and a general policy that will arrive at a good set of decisions.

Our views on the video game syndrome are reinforced by the findings by Jensen and Brehmer (2003). They used performance statistics on the regulation of a predator prey model that indicated that participants seemed to use an action sequence in decision making rather that referring to a [mental] model of the system. Somewhat similar findings were obtained by Martin et al. (2004). They found that, after playing the beer game 20 times, subjects were able to dampen oscillations typically found in net inventory. However, the investigators felt that some of the change in behavior was due to the subjects storing information about past experience and using that experience to predict future situations (Martin et al. 2004, p. 6).

3.2 Surveys or written tests

Surveys or written test are commonly used to access both knowledge and learning. Stave et al (2011) assessed the understanding of accumulation and flow in an introductory environmental science class using assignments and exams. Their work has progressed over five semesters, with revisions to both assignments and assessments. Initial findings indicate that "all students seem to understand the relationship between stocks and flows when flows are the same, but when flows are different, we found that students in the control group used the same erroneous pattern matching explanations that Sterman and Sweeney (2007) describe in their work" while those with previous training in accumulation showed better performance (Stave et al. 2011, p. 6).

In combination with causal loop exercises, Doyle et al. (1998) codified surveys to measure the number of causal and dynamic relationships before and after intervention. Their results indicate that an increased understanding about feedback was achieved. But they also report that subjects showed little change in the understanding of system complexity.

3.3 Comparison to Experts

Several interventions utilize causal loop exercises to measure the number of causal connections as compared to the number derived by an expert (Plate, 2010; Spector et al. 2001, Trabacaru et al. 2009). Trabacaru et al. (2009) tested four aspects of recognition including cues and non-salient factors, causal relations, goals, and decisions. They found that of the four aspects, "understanding seems to move towards more expert like understanding especially in the case of causal relations while the number of identified cues and non-salient factors remains largely constant" (Trabacaru et al. p. 14). They were unable to draw conclusions about changes in the quality of decisions.

3.4 Qualitative analysis and individual reflection

Huz et al. (1997) recommend domains for measurement. They used meeting minutes, archival analysis and informal reflections to capture systematically the modeling teams' reflections of the process. Their paper describes the evaluation design to capture shifts in thinking. They raised the question "what identifiable component of the intervention mattered most?" They discuss the issue of their measurement time frame and conclude that in "the short run, while the intervention is active, some changes in participants' thinking about the problem and some systemic changes do occur" (1997 p. 166). However they also note that their tests do not capture long-term impacts of system dynamics interventions. They then remind us to think about about the "regression away from systems thinking" over time (1997 p. 166).

Cavaleri and Sterman (1997) evaluated the change over time in business procedures at Hanover Insurance. Their evaluation made use of interviews, questionnaires, and evaluation of policies implemented after the initial intervention to measure both change in mental models and improvement in business. They found that managers who spent more time in intervention exhibited more systems thinking integration.

3.5 Transferability of Conclusions

Bakken et al. (1992) used a series of flight simulators then tested transferability of conceptualization and application of understanding of feedback/delay. They conclude that "to transfer successfully, people need to possess a generic framework as well as experience in its use" (p. 22). Spector et al. (2001) evaluated learning using questionnaires as well as causal mapping. Some subjects experienced a black box simulator with added information about structure while other subjects worked with examples of natural systems (deer population, growth and decline of yeast and spread of infection). The study concluded people learn best when they are actively involved in model building.[1] "Learners should be encouraged to engage in model alteration, model construction, and policy and strategy design in a collaborative context if one expects lessons to transfer from the learning environment to real-world settings" (Spector et al. 2001, 539).

[1] This finding will come as no surprise to teachers and consultants in the system dynamics community. Most would agree that model building and simulation is the ultimate path toward greater understanding. But this finding is not likely to be useful in power system training since trainees are not in a position to contribute to the construction of the underlying model.

3.6 Implications for System Dynamics Research

Many of the case studies described in the literature indicate limited learning but as noted earlier one should ask if this is a product of the design of the interventions or measurement tools. Many researchers have stated that their interventions were in fact limited by time and often reflect upon improvements for potential future interventions. Stave et al. (2011), in collaboration with Skaza and Trabacaru at the University of Nevada at Las Vegas are working to improve both teaching tools and evaluations through iterative development over multiple semesters (a common practice in other teaching and learning methodologies).

This long-term commitment to improving both teaching tool and assessment is an important contribution to the system dynamics community. In addition it is important that researchers recognize the impact of individual reflection and the delay in conceptual understanding when learning a new concept. Perhaps there was learning in the short, one-time interventions that did not manifest until days, weeks or months later when after reflection a similar situation inspired an *ah-ha moment*. Discussion and group reflection also aids learning. Designing more interventions that involve group exercises, a prominent and successful aspect of group model building, should also be explored as an aid to learning.

4. Implications for Research on Power System Training Methods

Although the system dynamics community is engaged in serious research to measure learning from model-based simulations and games, the insights from this research are not easily used to shape the mathematical methods on the role of power system operators. Four major differences limit the transferability of the methods and findings from the system dynamics community.

The first difference is stressed in the subtitle of the paper – the system dynamics interventions deal with time compression; the power system training relies on time dilation. Power system dynamics of interest in our research unfold in only a few seconds, and the mathematical models may simulate the dynamics with time constants measured in milliseconds. Control of these fast-paced dynamics is often dominated by automatic controls triggered by changes in deviations of power, frequency or voltage from the target values. The operators' role and the operators' opportunity for training are fundamentally different than the human subjects that are exposed to model-based games in the system dynamics community.

A second, major difference involves the time spent in training of power system operators. These individuals have assigned duties that require extensive training and opportunities for updated training as the control systems change. These individuals spend considerable time in preparation before participating in experiments with model-based simulators (Smith 1985). Their time commitment stands in sharp contrast with the limited time devoted to most system dynamics interventions.[2] The time limitations in system dynamics research is the result of university classroom scheduling and the limited time in executive workshops.

[2] In some extreme examples, system dynamics tests of the subjects' knowledge are executed in only a few minutes. Such tests are usually designed to reveal the subjects' misperceptions about accumulation, delays and feedback effects.

A third difference involves the patterns of dynamic behavior under study. System dynamics can be put to good use to study a wide variety of dynamic patterns. A short list includes exponential growth, exponential decay, S-shaped growth, overshoot, and a variety of oscillatory patterns such as damped and growing oscillations (Ford 2009). A longer list would include the complex oscillation with period doublings and with infinitely long periods (ie, deterministic chaos). The most relevant dynamics in the power systems stability research are the common forms of oscillations. System dynamics models can help us understand if oscillations are growing (out of control) or if they are damped (and perhaps over-damped). System dynamics models can also shed light on more complex patterns like deterministic chaos (Sterman 1988, Mosekilde and Larsen 1988). Tables 1 and 2 list studies dealing with a variety of dynamic patterns, but oscillatory behavior is not the dominant pattern under study. Aside from the predator-prey example by Jensen and Brehmer (2003), the oscillatory examples are confined to measurement of learning by subjects that played the beer game.

Appendix A explains that the beer game research holds the most promise for insights and experiences that may be transferable to training of power system operators. The dominant pattern of behavior is damped oscillations, but the system can exhibit a wide variety of oscillatory patterns (i.e., growing oscillations, limit cycles and even deterministic chaos). The beer game research is also promising because of its widespread use in system dynamics education, the careful explanation of the average subject's behavior (Sterman 2000) and "hoarding" explanation of extreme subjects' behavior (Dogan and Sterman 2006). The oscillations in the beer game are induced by the students' ordering behavior, a pattern analogous to "pilot induced oscillations" when rookies begin training as aircraft pilots. There are some situations when "operator induced oscillations" appear in the power industry, but the situations that we are aware of do not involve serious threats to the stability of the regional system.

In our view, however, the potential for transferable insights is limited by the time issues mentioned previously. The beer game acts to compress time, whereas power training simulators act to dilate or stretch time. Also beer game subjects conduct their experiments and achieve their learning in a very brief time interval compared to the time available for training subject in the power industry. Finally, and perhaps most importantly, electricity is fundamentally different from a storable products (like beer held in inventory). The physical properties of the power system require the demand for electric power to be satisfied simultaneously across a complex grid. The physical properties also demand sophisticated control procedures to limit the loss of service when the system is unable to satisfy demand. Simulating these physical properties is at the core of the mathematical models used in power system simulators.

Conclusion

New methods are needed to represent human decision making along side of complex power system models of the physics of a large interconnected time-variant grid system. The system dynamics community has a long history of simulating human decision making within a model of the 'physics' of the larger system. The community has also been working seriously to measure the learning from subjects that use model-based simulators. However, our review indicates that the findings from the system dynamics work are not easily transferred to the development of improved mathematical methods to simulate short-term grid operations in the power industry.

The ultimate goal of our current research project is improved models for the simulation of power system stability, including situations with a significant role for the human decision making. A possible avenue for further research may build from recent system dynamics simulation of the challenges of integrating more wind generation into the Pacific Northwest power system. A system dynamics model was used to explore increased use of pumped storage facilities at Lake Roosevelt. Appendix B describes this application as a promising use of system dynamics simulation of minute-by-minute operations of a narrowly defined piece of the power system. Although the model delivered useful findings for the operation of the pumped storage, it is not a useful point of departure for further research on advanced mathematical methods for the study of large interconnected power systems.

Appendix A. Lessons from the Beer Game

The beer game is widely known within the system dynamics community, especially in business education. The first version of the game was created in the 1960's to demonstrate principles of supply chain management. Players aim to meet customer demand by ordering product in the multi-stage supply chain depicted in Figure A-1. Their goal is to minimize inventory costs but to maintain sufficient inventory to fill incoming orders. The game has been played by teams of undergraduate students, graduate students, teachers and business executives. The intriguing result is that all teams exhibiting volatile oscillations in orders and inventory. The oscillations would be a serious problem in a real distribution system, especially as their magnitude is amplified as we move from wholesale to distribution and from distribution to the factory. The oscillations come as quite a surprise to the players since there are no disruptions of supply (i.e., due to strikes or factory problems). Also, the factory can deliver any amount of beer, no matter how large the orders. But there are delays for the beer to travel through the supply chain. The game reveals that dealing with these delays is quite a challenge, even for seasoned business leaders participating in executive education programs.

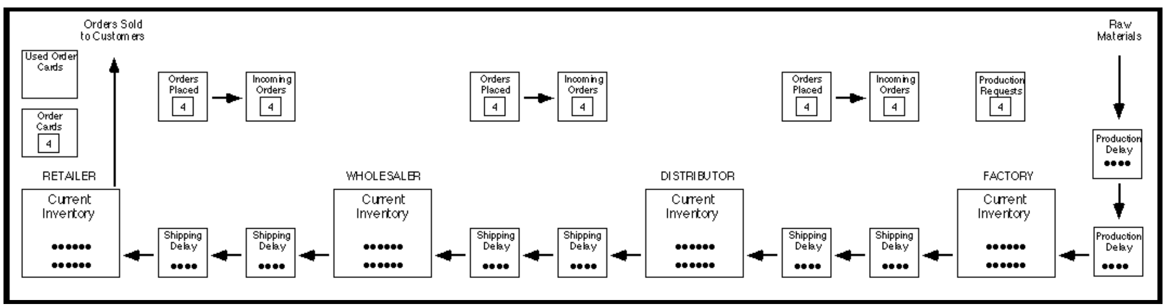

Fig. A-1. Initial conditions of the beer game.

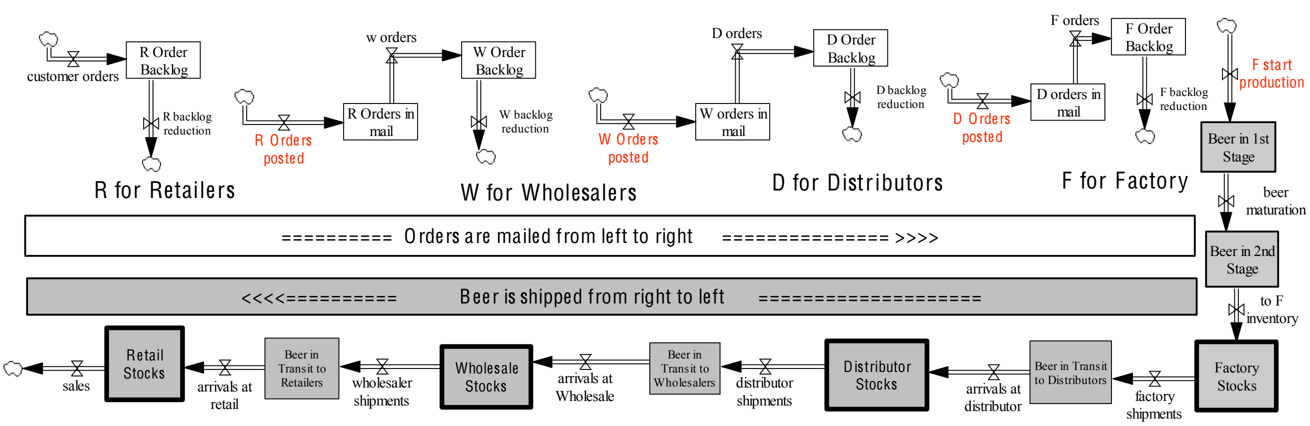

Fig. A-2. Stocks and flows in a system dynamics model of the beer game (Ford 2009, p. 253)

Figure A-2 shows a system dynamics model designed to represent typical decision making by subjects that played the game. This diagram concentrates on the stocks and flows – the physical aspects of the system. Adding the human decision making observed in the game leads to a model that reproduces the oscillations that appear in the game. The key to capturing the players' behavior is to represent their failure to account for the effect of previous orders that have not led to product received in inventory. This missing product is sometimes called product "in the supply line" (Sterman 2000, p. 695). Statistical analysis of subjects' ordering decisions revealed that they appear to count only around a third of the product in the supply line.[3] This tendency to ignore the supply line creates boom/bust patterns in a wide range of industries, especially in industries like real-estate and electric power where planners face long delays for the construction of new capacity (Sterman 2000, Ford 2002, 2009)

The beer game oscillations are also instructive in thinking about oscillatory behavior that unfolds in just a few minutes of time. For example, one student found the beer game oscillations to be similar to pilot induced oscillations in an aircraft. The student was a pilot, so he knew first-hand that trainees often over-steer the aircraft, creating growing oscillations. Aircraft flight simulators are part of the training to help pilots develop instincts for flying a real aircraft. These flight simulators are an excellent analogy to power system training simulators. In both cases, the goal is help to help humans avoid contributing to growing oscillations

Growing oscillations are certainly a serious problem in the electric power industry, as indicated by the August 1996 blackout on the west coast.[4] In this major event, oscillations in power (MW) at the California-Oregon Intertie appeared with a 4-second period and grew out of control within around 80 seconds. This major event was notable for the disruption in homes and businesses affecting 4 million people. It was also notable for the fact that industry models were unable to simulate the growing oscillations (Kosterev 1999).

Although this major system failure was difficult to understand, investigators have not characterized the problem as similar to pilot induced oscillations in an aircraft. On the other hand, some narrowly defined power systems have experienced oscillations that were made more difficult by the human decision making. These examples might be described as "operator induced oscillations," oscillations analogous to those that appear in the beer game. However, these examples do not involve major outages, and the oscillations were not perceived as a serious problem.

For these reasons, and for the reasons stated previously, we conclude that lessons drawn from the beer game are not likely to be useful in our effort to develop improved mathematical methods to simulate short-term grid operations in the power industry.

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[3] A surprisingly similar result was found in analysis of the boom/bust pattern of construction during the California electricity crisis of 2000-2001. A system dynamics simulation of investor's behavior was able to reproduce the size of the construction boom (Ford 2002). But the historical fit required that the simulated investors count only a third of power plants under construction as likely to contribute to future estimates of reserve margins and likely wholesale market prices.

[4] The 1996 west coast blackout is described at websites maintained by the Northwest Power and Conservation Council and by Wikipedia. Wikipedia also provides information on wide-scale blackouts.
http://www.nwcouncil.org/history/Blackout.asp
http://en.wikipedia.org/wiki/1996_Western_North-America_summer_blackouts
http://en.wikipedia.org/wiki/List_of_power_outages

Appendix B. Simulating Wind Integration from Pumped Storage

This appendix will show an example of how system dynamics can improve understanding of short-term operations of the power system with increased wind generation. A system dynamics model was constructed by Tyler Llewellyn (2011), a WSU graduate student, to simulate water flows between Lake Roosevelt and the Banks Lake impoundment at higher elevation. The facility, known as the Banks Lake and the John W. Keys III Pump-Generating Plant (BLK), is operated by the Bonneville Power Administration (BPA). Llewellyn worked closely with WSU faculty and with BPA staff to design a system dynamics model for realistic simulations of BLK operations . The model simulates time in minutes, with a simulation running for 10,080 minutes to cover a typical week of operations. The model examines different ways to operate the pumps and turbines at the BLK to provide incremental reserves and decremental reserves for wind integration. His simulations indicate that

- the BLK could provide most of the balancing reserves demanded by current wind power development,
- irrigation withdrawal requirements are not adversely impacted by wind integration operations, and
- changes to current irrigation operations could enhance BLK's ability to supply balancing reserves for wind integration without impacting its ability to meet irrigation withdrawal requirements.

This appendix provides a brief description of the model structure and simulation results. The appendix concludes with the potential contribution of this type of modeling toward our research on advanced mathematical methods for large, interconnected power systems.

B.1 Model Structure

The hydrologic stocks and flows are depicted in Figure B-1. This diagram is drawn with the Vensim software, one of the common stock-and-flow programs for implementing system dynamics models. Llewellyn implemented his model in Stella (another popular stock-and-flow, icon based program) taking full advantage of Stella's many interface features to facilitate easy simulation with multiple scenarios and policies.

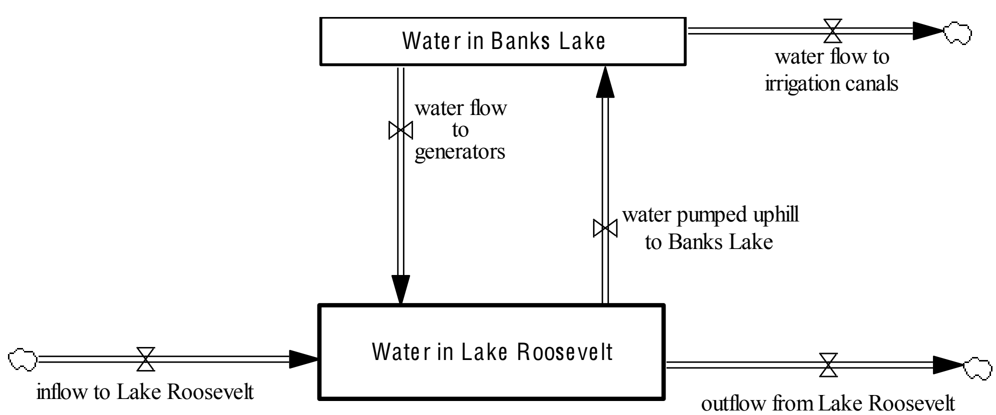

Figure B-1. Water flows and storage at the pumped storage facility.

As with all system dynamics models, the pumped storage simulator is a collection of coupled, nonlinear, first order differential equations. The equations are simulated through numeric Methods. (The model uses the Euler method with a time step of 1 second.) Figure B-2 helps one envision the underlying differential equations. The long variable names from the previous diagram are converted to single letters to allow for easier display of the differential equations:

$$dW1/dt = f1 - f2 - f3$$
$$dW2/dt = f2 + f4 - f5$$

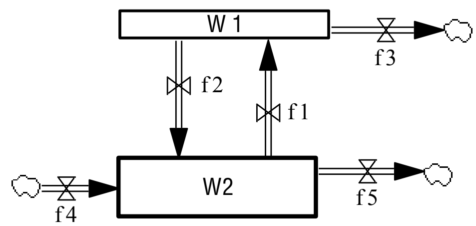

Figure B-2. Recreation of the previous diagram with short variable names

These diagrams provide a glimpse of the model structure. Additional stocks and flows are used for posting of MW of wind capacity to an hourly schedule. Other stocks and flows keep track of the electric energy implicitly stored by the water in Banks Lake.

<u>B.2 Illustrative Results</u>

Figure B-3 shows BPA wind fleet generation and hourly wind schedules over one week Nameplate wind capacity was assumed to the approximate the 3,000 MW of capacity in 2010. Wind generation capacity factors reflect actual BPA wind fleet five-minute capacity factors recorded during June 7 through June 13, 2010, a week known as a "high-water event" on the Columbia River system. Thus, the base case simulation shows the flexibility provided by BLK-supplied balancing reserves during a week when additional flexibility is highly valuable.

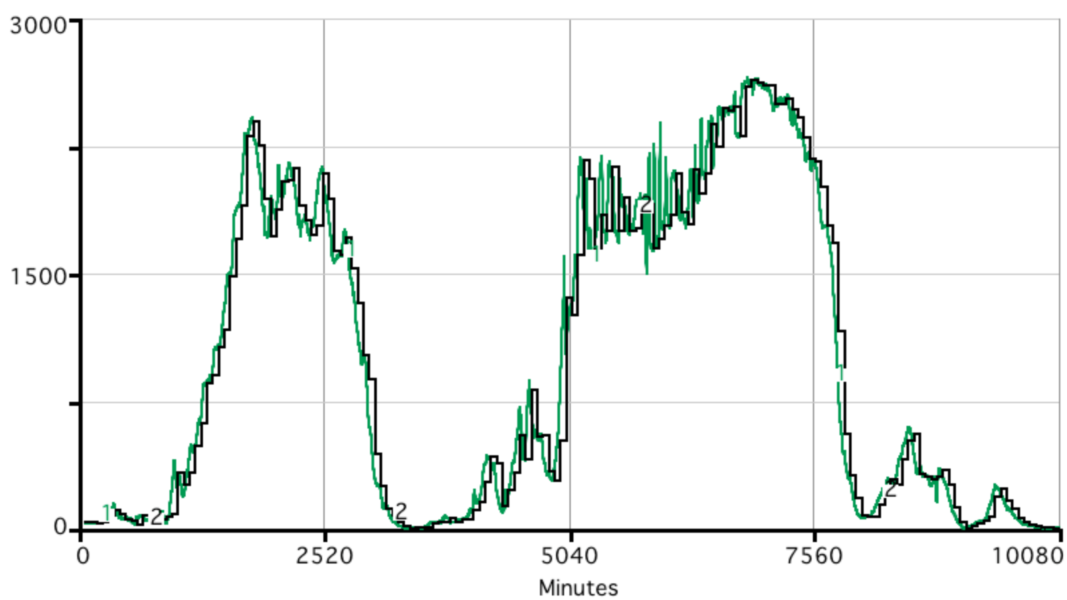

Figure B-3. Actual wind generation (in green) and scheduled wind generation (in black) during a week of high water flows and hourly scheduling in a 30-minute persistence scenario. (Results are displayed with the vertical axis scaled from 0 to 3,000 MW.)

Wind generation is shown by the green line in Figure B-3. It fluctuates dramatically from a minimum of zero to a maximum of approximately 2,700 MW during the week simulated. The time period also includes two very large up ramps and down ramps in wind generation. The wind schedules (black line) reflect 30-minute persistence forecasting accuracy. Thirty-minute persistence wind schedules are consistent with *BPA 2010 Resource Program* and *2012 BPA Initial Rate Proposal Generation Inputs Study* analyses. Thirty-minute persistence wind schedules are utilized in BPA analyses as they are approximately equivalent to current wind schedule forecasting accuracy. The difference between wind generation and wind scheduled at any time is the wind station control error, and thus determines the demand for incremental and decremental reserves from the BLK.

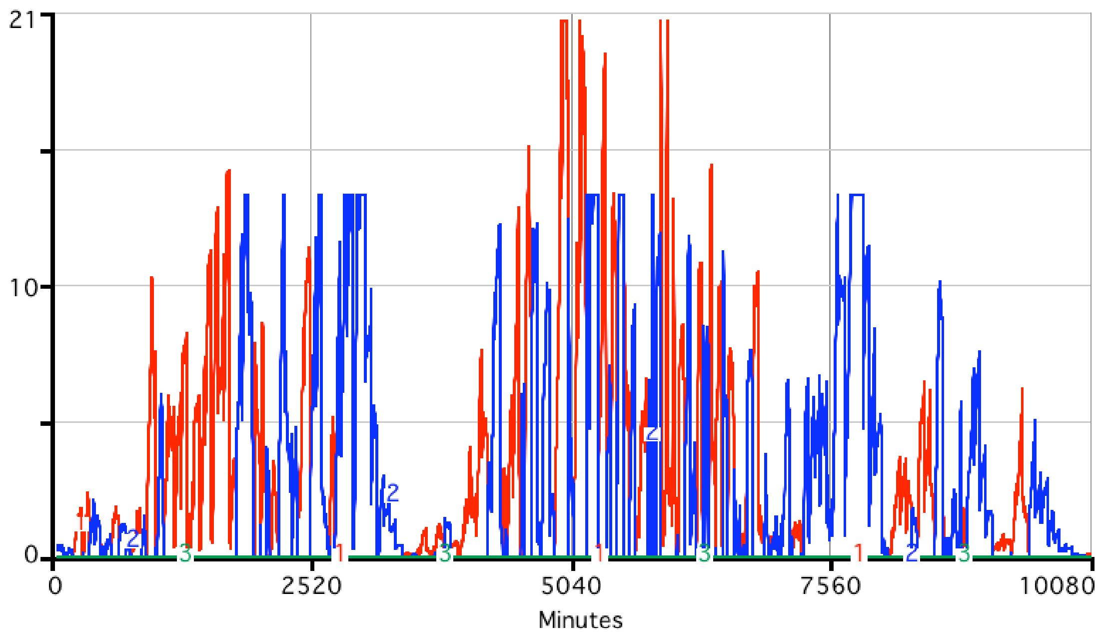

Figure B-4. Pump flows (in red) and generator flows (in blue) during a week of high water flows and hourly scheduling in a 30-minute persistence scenario.
(The flows are displayed with the vertical axis scaled from 0 to 21 KCFS.)

Figure B-4 shows the BLK switching rapidly between pumping and generating to provide the reserves needed for wind integration:

- Decremental Reserves: The pumps are run to pump water uphill to Banks Lake (see the red line in Figure B-4.) The electricity consumed by running the pumps provides the decremental reserves needed when wind generation exceeds its schedule.
- Incremental Reserves: The generators are run when water is released from Banks Lake to flow downhill to Lake Roosevelt (see blue line in Figure B-4). The electricity generated by the turbines provides the incremental reserves needed when wind generation is less than the scheduled amount.

Both the maximum pumping and generating capacities were reached in this base case simulation. The maximum pumping capacity is 20.72 KCFS, equivalent to 600 MW. The maximum pump flow was reached four times in this simulation. The maximum generating capacity is 14 KCFS, equivalent to 314 MW. The maximum generator flow was reached approximately 10 times in this simulation The maximum pumping and generating capacities are generally reached during the large up and down ramps in wind generation.

This base case simulation demonstrated that a high percentage of incremental and decremental reserves can be supplied through operating BLK for wind integration. Indeed, the BLK could provide approximately 90% of incremental reserves and 99% of the decremental reserves needed for wind integration during the simulated week.

B.3. Simulation Scenarios

The pumped storage model is notable for the easy selection of different scenarios and policies for simulation. For example, the user can select from different scenarios for errors in wind scheduling.

- *Perfect Schedule*: For clarity of interpretation, the easiest scenario is the perfect schedule, a one-hour schedule that equals average generation over the hour. The energy generated over an hour equals the energy scheduled over that same hour. This simulation demonstrates that BLK would be heavily used even under "perfect" conditions.

- *Thirty-Minute Persistence Schedule*: This scenario was used to get the results in Figures B-3 and B-4. This is a one-hour schedule based on the actual wind fleet generation thirty minutes prior to the beginning of the hour. (Thirty minute persistence scheduling accuracy is the wind forecasting accuracy assumed in BPA Rate Case and Resource Program modeling.)

- *Actual Schedule*: The user can also select the actual schedule from the week of June 7-13, 2010. This scenario gives the one-hour schedule that represented the actual hourly forecast for the BPA wind fleet over the hour.

The model also allows for easy selection of different scenarios for the irrigation operations.

- *Replacement Pumping*: The replacement scenario calls for the pumping schedule intends to pump water into Banks Lake at the same rate at which is it being released to the Columbia Basin Project.

- *Minimal Cost Pumping*: A scenario to minimize pumping costs aims to pump water into Banks Lake during times of lower electricity prices, which occur during light load hours at night from 10 pm to 7 am and all day Sunday.

- *Maximize Reserves Pumping*: The model may also be operated which the pumping schedule aims to pump water into Banks Lake during heavy load hours, which occur from 6 am to 10 pm Monday through Saturday. Simulations with this scenario revealed that pumping during the middle of the day maximizes the total amount of incremental reserves that can be provided by Banks Lake during heavy load hours. Further, this irrigation pumping schedule maximizes the total decremental reserves provided by Banks Lake during light load hours.

B.4. Conclusions from the Wind Integration-Pumped Storage Model

Llewellyn's simulation analysis led to important findings for the operation of the BLK pumped storage facility. For example, simulates indicated that a modernized and upgraded BLK could provide significant incremental and decremental reserves for wind integration without impacting the ability to meet irrigation withdrawal requirements. And if the irrigation operations so incremental and decremental reserves are held over all hours improves the ability of BLK to provide balancing reserves for wind integration and reduces switching between pumping and generating modes. However, if the reserves for wind integration are provided entirely from solely from the BLK, operators should expect to see continual rapid dispatch of pumping and generation. The model also showed that supplying reserves for wind integration could slowly draft Banks Lake in simulations without additional pumping to maintain Banks Lake storage.[5]

B.5. Implications for Research on Advanced Methods

The pumped storage model is a promising application of system dynamics to deal with operational dynamics that unfold on a minute by minute basis. Indeed, the model is the best example of a system dynamics modeling with relevance to the challenge of maintaining stable operations in the electric power system. The model delivers pragmatic and useful results, but it is not directly relevant to our interest in the role of human decision making. The current model represents the schedules posted by humans, but it does not involve an explicit simulation of their decision making. An interesting avenue for further research is expansion of the pumped storage model represent different decision making strategies by the wind company officials for posting the generation schedules.

However, for the overall purposes of our research project, the pumped storage model is not a useful point of departure for further research on advanced mathematical methods for the study of large interconnected power systems. The model is limited by its treatment of a single facility and it does not deal with the complex mathematical challenges of representing multiple generations, multiple loads, and multiple transmission lines. The model does not deal with control center operations, nor does it simulate variable such as bus voltages and line power flows. And finally, the model does not simulate rapidly changing dynamics (ie, changes that would be displayed in seconds rather than minutes).

[5] The net removal of water from Banks Lake is caused by the round-trip efficiency loss associated with pumped storage. (The energy to pump water uphill is larger than the energy generated when the water flows downhill.) The drafting of Banks Lake would occur during a time period when the demand for incremental reserves matches the demand for decremental reserves.

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