Simulating the long-term or the short-term? Dare we do both?

Lessons from Policy Simulations in the Electric Power Industry

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Abstract

This paper deals with the choice of reference modes in system dynamics modeling. Do we aim for a simulation of long-term dynamics, or should we focus on the short term? A common suggestion is to face up to this difficult question and not be diverted by the illusion that you can do both. This paper explores a new direction by describing methods to simulate long-term and short-term dynamics in a coordinated manner. The methods emerged during three studies of the power industry. Each study focused on important policy issues at the time, and each study required simulations of short-term and long-term dynamics. The policy findings summarized here provide background on the methodological challenges. The methods described here will be useful to those who dare to include dramatically different time dynamics in their simulations.

Introduction

This paper addresses the challenge of simulating systems with a mix of fast-acting and slowly developing dynamics. A common question is whether to focus on the long-term or the short-term. This question should arise early in the modeling process when the team assembles to discuss the reference mode.[1] Imagine a team meeting where some argue for a short-term model that simulates a one month interval with time in hours. Others may argue for a simulation over a thirty year interval with time in months. Imagine that the two view points are well represented, and the client turns to you for advice. Which would you recommend?

Systems dynamics has certainly been put to good use in simulating long-term trends, especially when the models show the effect of long delays in key feedback loops.[2] The long-term choice also makes sense when systems are prone to "worse before better" (Forrester 1961, p 349) or when long-term goals conflict with short-term goals (Forrester 1994, p 18). So there are good reasons to recommend the long-term model and coax the client group to put short-term concerns aside for the purposes of better understanding.

This paper describes situations where the short-term dynamics are not easily pushed aside. Indeed, the short term dynamics may be crucial to our understanding of long-term trends. This

[1] The reference mode is the target pattern of behavior; drawing this target pattern is perhaps the most important step in the modeling process (Sterman 2000, p 90; Ford 2010, p 50).

[2] A long-term perspective comes to mind when reflecting on major accomplishments such as *World Dynamics* (Forrester 1971) and *The Limits to Growth* (Meadows 1972).

situation calls for two models, but which should we build first? With ample resources, we might succeed in building both models. Then we face another challenge: how to make good use of two models with dramatically different time horizons?

One approach is to fuse the models into a single model with a long time horizon and a time step sufficiently small to ensure accurate simulations. The end result would be accurate, but sluggish simulations. Slow simulations are tolerated by some, but we should avoid them if we want to maintain client engagement in interactive demonstration of model results.

Some will point to improvements in computing power as the answer to the sluggish simulations, but this paper points in a different direction. The key to effective use is not faster computers; it is learning the key insights from the short-term model and finding a way to incorporate the insights in the long-term model. The goal is a pair of models with realistic dynamics and the speed and clarity needed to sustain client engagement.[3]

Policy Simulations from the Electric Power Industry

The approach described in this paper emerged from studies of temporally complex situations in the electric power industry. Each study delivered policy relevant insights, and each model simulated a mix of short-term and long-term dynamics. But the models employed entirely different methods, as summarized below:

1. The first study was performed for the California Energy Commission (CEC) to provide better understanding of the energy crisis of 2000-2001. The CEC asked for a system dynamics model to include fast-acting wholesale price spikes within a theory of boom and bust in power plant construction. The CEC was quite specific about the price dynamics: they should be displayed in chronological fashion, a change from the load-duration curves commonly used in previous decades.[4] Load duration curves were discarded, and a compressed, chronological calendar was created to meet their needs. The new model delivered insightful results, but it did not deliver the fast simulations needed for interactive demonstrations.[5]

[3]Informal feedback from my clients suggests that speed and clarity are powerful AND unique features of system dynamics. In the words of one enthusiastic client: *these simulations are like nothing we have seen before*.

[4] A common practice in the 1980s and 1990s was to simulate power system operations with generating resources stacked under a load duration curve. The curve is a statistical summary of the loads, with the annual peak at zero duration and the minimum at 100% duration. Generation from different technologies was based on their position in a stack under the curve. The method was popular despite the errors near the peak point and the minimum point of the curve. These errors were of little concern in many studies, but they were not to be ignored when electric vehicle issues emerged in the 1990s. The vehicles' night-time charging placed extra load exactly in the problematic portion of the load duration curve. This problem was overcome in our system dynamics models by dispatching generators under a rotated load duration curve, with the rotation selected to match the detailed production costing models used by a major California utility (Ford 1994).

[5] The calendar called for 4 typical days/yr and a 12-year simulation;, so a simulation covered 1,152 hours. The Stella Run Specs defined Time in hours with DT = 1/16th of an hour; a simulation required 18,432 time steps. Stella buttons were placed on the time axis in graphs to aid in interpreting the complicated calendar.

2. We turned to NSF to support development of a better approach. The goals were more detailed representation of the interconnected power system in the western United States and faster simulations with a more natural representation of time. The new model simulated a typical day in each month from 2005 to 2025. Hourly results were represented in array variables with 24 elements to show changing conditions for each day. The methodological benefit emerged when the 20-year simulations appeared with much greater speed than the 12-year simulations in the California study.[6]

3. The third study was performed for NRStor, Inc. a storage development company in Toronto, Ontario. The models showed the value of a storage facility by simulating the benefits to Ontario rate-payers over 30 years. The study began with load leveling, a commonly discussed use, but one which delivered surprisingly little value. We then turned to the use of storage to provide Ontario's growing need for wind integration. The temporal complexity changed dramatically since wind integration could only be addressed with several models operating with entirely different measures of time.[7] With the coordinated use of multiple models, we achieved the speed and clarity needed to sustain interest in the model demonstrations and the storage results.

These studies are described in full detail in previous publications with emphasis on the policy-relevant results. The policy results are summarized briefly below, followed by explanations of the methods used to simulate the mix of short-term and long-term dynamics.

[6]The faster simulations were achieved with a different calendar, i.e. a typical day in each month for a 20-year simulation. The Vensim model settings defined time in months, with DT = 1 month, so a simulation required only 240 months and 240 time steps. Vensim's Time Axis/Time Base tool was used for graphs clarity. Hourly results for typical days were exported to spread sheets to see the daily dispatch graphs often used in the power industry.

[7]The long-term model ran for 30 years with time measured in months using the 24-element arrays, as in the NSF study. The short-term model ran for 7 days with time in hours and DT = 1 hour, so a simulation required only 168 time steps. A third model ran for 7 days with time measured in minutes to keep track of INC & DEC reserves. It required over 10,000 steps and 1-2 minutes to simulate, a bit slow for interactive demonstrations, but simulation speed was not a problem as the model was only used to establish a proxy for wind generation forecasting errors.

Construction Dynamics in the California Energy Commission Study

The key results from the California study are summarized with images from the workshop presentation (Ford 2001B), starting with construction in Fig. 1 and the theory of investor behavior in Fig 2.

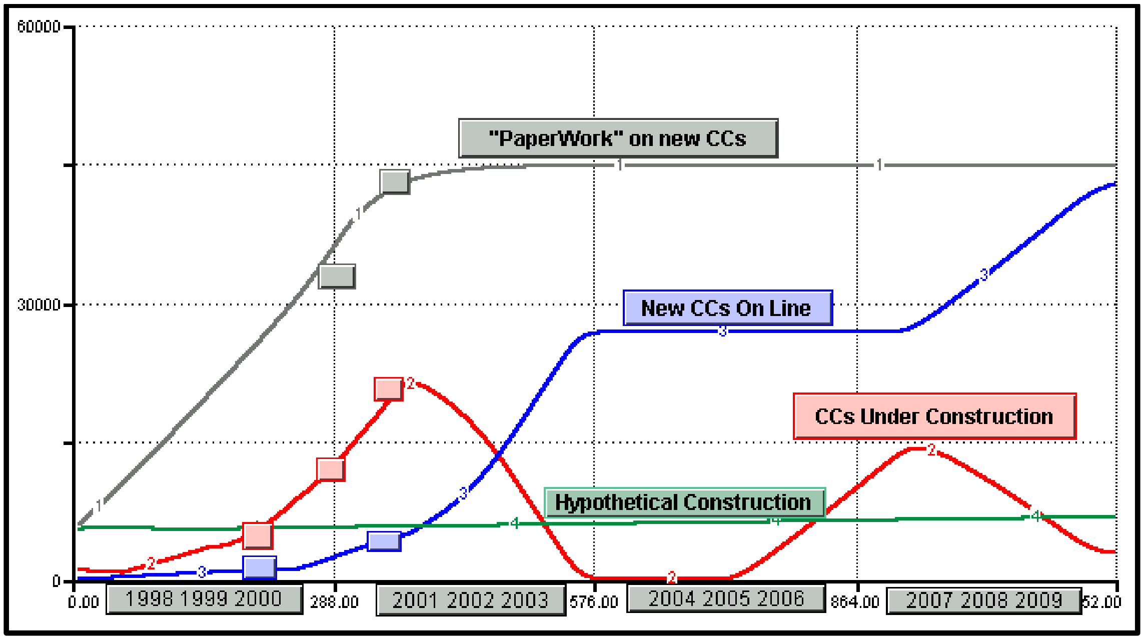

Figure 1. Base case simulation shows boom and bust in power plant construction.

Fig 1 shows the simulated pattern of boom and bust along with the construction needed to keep pace with demand. The graph depicts under building in the first three years, followed by a major building boom that peaks around 2001. Buttons are positioned on the interior portion of the graph for comparison with historical information.[8] Fig 2 shows the theory that gives rise to boom and bust. The process begins with construction permits which reached incredibly high levels.[9] The crucial decision was whether to start construction. Fig. 2 describes the simulated decision with illustrative numbers from1998-1999, the period when construction projects were insufficient to keep pace with growing demand. AB 1890 replaced the IOUs' obligation to serve with the expectation that a wholesale market could send price signals to stimulate an appropriate amount of construction. Working through the numbers reveals that the power system would be dangerously low on reserves even in the absence of boom & bust.[10]

[8] The buttons proved quite useful, with the construction buttons drawing the most interest. The base case projected the first boom to peak shortly after the workshop. The four buttons on the time axis translate Stella months into the 12 years from 1998 through 2009.

[9] Paperwork is the sum of pending and previously approved permits in the site bank. It reached nearly 45,000 MW in 2001, enough permits to support 16 years of construction needed to serve demand.

[10] The 15% reserve margin is a common target for reliable operation, but the market price would not cover levelized costs. So investors would wait for growth in demand and higher prices. Eyeballing the curve shows they would wait for the reserve margin to fall to 8%, just above the 7% for a stage one alert. Fig 2 reveals that AB 1890 would eventually deliver a system with dangerously low reserves even in the absence of boom and bust.

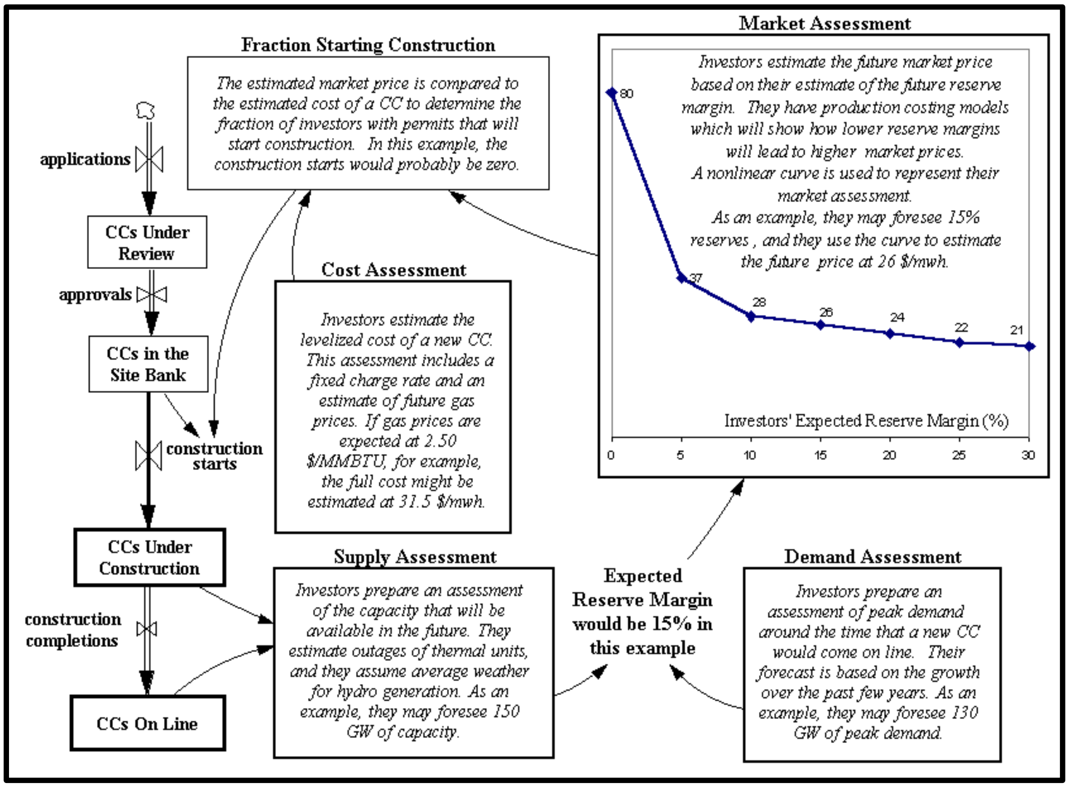

Figure 2. The Theory of investor behavior in the western market model.

Like investors in other competitive industries with long lead times, power plant developers in California were prone to boom and bust, as indicated by the results in Fig. 1. The model provides a good explanation of both the under-building in 1998-1999 and the overbuilding in 2000-2001.

Most of the model parameters were easily estimated from data on demand growth, permitting lead times, construction lead times and the general shape of the wholesale market price curve.[11] The difficult parameter was the fraction of CCs plants under construction that investors included in their supply assessment. The history of boom and bust in industries with long lead times indicates that investors fail to give full attention to the projects in the construction pipeline.[12] Interviews with experts in California and the Pacific Northwest revealed a wide range of opinions. Some suggested that almost all the plants under construction would be counted in

[11] Serious investors would have the tools to calculate a market price curve like the one in Fig 2. My own curve was generated by the spot market portion of the western model, so it was consistent with spot prices that would appear in simulations of a competitive wholesale market.

[12] The supply assessment looks two years ahead, the same as demand assessment. CCs require two years to complete construction, so one might expect investors to count 100% of these power plants in the supply assessment. Giving full weight to the construction in the pipeline may be rational thinking, but evidence from construction cycles suggests that investors do not pay full attention to construction in the pipeline (Sterman 2010, p 698).

investor's supply assessments. Others suggested that only 25-50% of the power plants would be counted. We selected a 50% weight as it gave the best fit with historical construction.[13]

Simulated construction peaked in 2001, followed by a smaller boom 6 years later. The second round of under/over building confirmed that the pattern arises from the internal structure of the system.[14] We see damped oscillations with constant inputs; with random variations included, we could expect a continuing, but irregular pattern of boom and bust.[15]

Spot Price Dynamics in the California Energy Commission Study

The theory of wholesale market behavior uses the stock adjustment process in Fig 3. The outer loop keeps track of the electricity demand that is influenced by changes in the retail price. The market model focuses on the wholesale price of electric energy (in $/MWh) which is best estimated with a fractional adjustment due to generators ability to bid into the ancillary services market as well as the energy market.[16] The outer loop provides delayed and weak control, as it must act through retail prices. The inner loop is an entirely different story. It acts incredibly fast to provide operational control of prices to ensure that electricity generation is sufficient to meet demand. Under regular operations, for example, the price might double in a one hour interval to bring more expensive units into operation. An accurate numerical integration might require 8 steps per hour, so a typical day would require 192 steps and a single year nearly 70 thousand steps. The challenge is even more difficult with 20-fold or 40-fold price increases.

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[13] System dynamics readers may put the 50% weight in perspective by recalling the product distribution game used in business school classrooms (Senge 1990, p 40; Sterman p 684). The role-playing exercise reveals a natural tendency for participants to undercount the previously issued orders. Statistical analysis by Sterman (2009, p 693) inferred the weight given to the pipeline at 34%. I found the 50% versus 34% comparison reasonable when thinking about real investors in the power industry versus role-players in the classroom. But my instincts were proven wrong two years later when the CEC asked for updated simulations to represent changes in exogenous inputs and to simulate the actual construction boom which had continued to climb past the 2001 peak in Fig 1. A new weight was needed, and simulation experiments showed a 35% weight provided the best fit with historical construction. The updated model showed oscillations with a longer period and less dampening.

[14] Some participants were inclined to attribute boom and bust to exogenous disturbances, but the base case was free of such disturbances. Others attributed the poor behavior to early market jitters. They argued that the appearance of the second round of boom and bust invalidated the model. (In their words, the model made investors look stupid.) This attempt to dismiss the findings was not widely supported partly because many saw the strong analogy between power plant construction and real-estate construction (where boom and bust have persisted for over a century (Hoyt 1933, Sterman 2009, Ford 2010)).

[15] Random inputs can turn damped oscillations into growing oscillations that will eventually form a limit cycle. With continued random inputs, we will see an irregular limit cycle, as illustrated by Ford (2010, p 263).

[16] The model used a 7% increase to create an effective demand. The generating resources are simulated to serve the effective demand, and the price is taken as an approximation for the energy price that would result when generators can bid into both markets (Ford 2001B, Hildebrandt 2000).

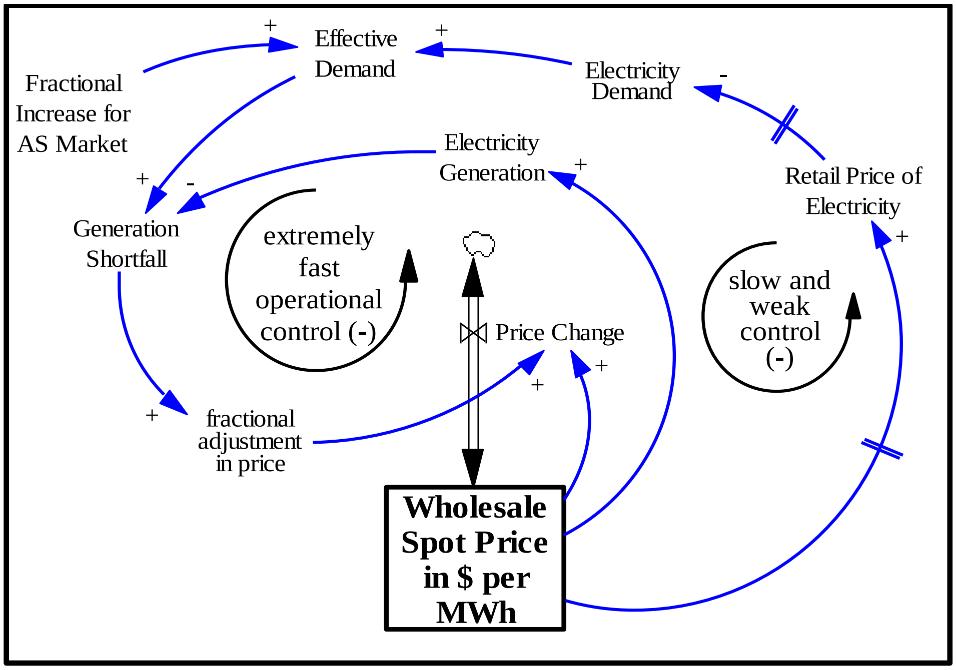

Figure. 3. Stock, flow and feedbacks to represent spot price dynamics.

The challenge was to simulate the extremely rapid changes in spot prices within a 12-year model of construction. Meeting this challenge confirmed that *necessity is the mother of invention*. We invented a new calendar with four days per year. The simulations began with a typical day for winter, followed by typical days for spring, summer and fall.[17] Time was defined in hours, so the 12-year simulation required 1,152 hours. With DT at 1/16th of an hour, each simulation required over 18,000 steps and 2-3 minutes on my laptop. Such simulations are too slow for interactive demonstrations where we would hope for suggested simulations to appear 2-3 seconds after moving the sliders. But the simulation speed was adequate for the CEC study since results were produced in advance of briefings. With some patience, we developed useful simulations, starting with the base case results in Fig 4.

The first two years in Fig 4 showed familiar spot price behavior; hourly prices varied from around 20 to 40 $/MWh as the model simulated typical days in each quarter. The average annual prices were somewhat below the levelized cost of new CCs. The price dynamics changed dramatically when the first price spike appeared in the Spring of 2000. This was followed by off-the-chart spikes in the Summer and Fall of 2000, the Winter and Spring of 2001. The final spike appeared in Summer of 2001. Quarterly average prices reached a high of 250 $/MWh, far above the levelized cost of new power plants. The simulated quarterly prices from 1998 through the summer of 2001 were similar to prices reported by the California ISO (Ford 2001B).

[17]Four days may seem inadequate to summarize prices over an entire year, but the compressed calendar proved sufficient to show a good match with the historical quarterly average spot prices The 4-day calendar was also sufficient to show spot prices in the absence of "economic withholding" that were a good match with the "counterfactual prices" published by the California ISO.

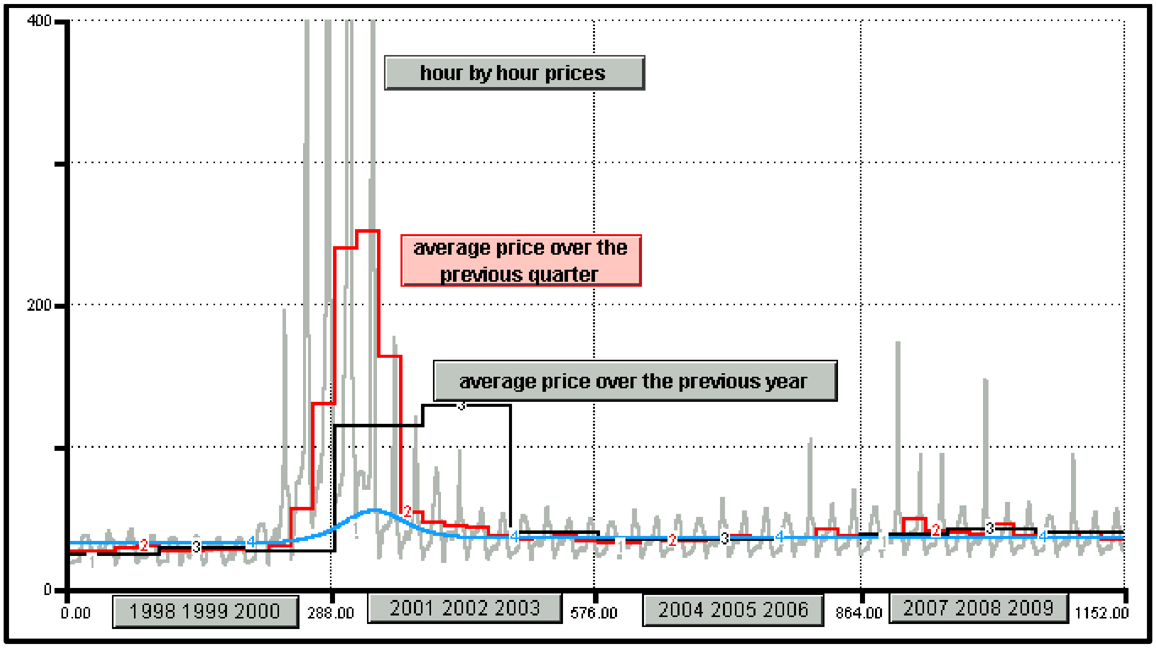

Figure 4. Base case wholesale spot prices ($/MWh) with the levelized cost of CCs in blue.

The key assumption in matching the historical record was the simulation of the generators' "strategic behavior" in the wholesale market. Investor behavior during periods of tight reserves was often described as capacity withholding or economic withholding. The presence of strategic behavior was made clear in ISO reports comparing actual prices with estimates of the counter-factual prices that would appear in a competitive market. We elected to use economic withholding as a proxy for the combination of measures available to generators to influence the price when reserves were tight. The key input was the fraction of gas-steam plants in California that bid into the wholesale market at prices beyond variable costs.[18] This form of strategic behavior was successful in generating prices to match the ISO reports. The match with historical behavior built confidence in the model despite the unusual calendar with only 4 days per year. Confidence was further strengthened when the model provided a good fit with the ISO counter factual prices when the fraction engaged in economic withholding was set to zero.

Turning to the second half of Fig 4, we see a reappearance of price spikes in 2006-2007. The price spikes are much lower than historical price spikes, but their timing is similar.[19] The second round of price spikes are modest by comparison, but they reveal a new situation on the edge of crisis conditions.

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[18] Economic withholding occurred in hours with tight reserves, as they provided the best opportunity to exercise market power. These generators would submit bids ranging from the upper limit on true, variable costs to the price cap. The fraction of generators withholding was a controversial user input, as was the price cap. The market operated without a formal price cap, but experts spoke of a "soft" or informal price cap, commonly said to be $1,000 per MWh, thought to be the limit of utilities willingness to purchase energy.

[19] The spikes in 2000 and 2001 appeared in the midst of a large building boom, just prior to the majority of the new CCs completing construction. The spikes in 2006 and 2007 appear in the midst of the second building boom, just prior to the next major increase in installed capacity.

The potential for a second crisis was explored with changes to allow 2006-2007 conditions to be similar to conditions in 2000-2001. These involved changes in hydro-electric generation and a return to the price cap policy from 2000-2001. The new simulation revealed that the western system could be "one dry year away" from a repeat of the crisis conditions that appeared in 2000 and 2001. Without fundamental changes, policy makers would expose the west to another round of price spikes and rolling blackouts. The model was then used to explore proposals to avoid a repeat of the California electricity crisis.[20]

The NSF Project

The NSF project was funded to improve upon the calendar and simulation speed of the CEC model. The project also developed new methods to simulate transmission system interconnections. Methodological issues are discussed by Dimitrovski (2007) from a power system engineering perspective as well as a system dynamics perspective. Once the new methods were tested, the model was used to stimulate the reduction in CO_2 emissions that would follow the adoption of the carbon market proposed in SB 139 (Ford 2008).

Fig 5 shows the opening view of the new model. It provides navigation to model diagrams in grey, model results in green. The links to the demand and spot price views remind us of the operational control loop in Fig. 3. The most important challenge was to reformulate the model to avoid sluggish simulations. Simulations will be faster if we can avoid the small DT, as in DT = 1/16th of an hour to simulate price spikes. But a small DT is necessary for numerical accuracy in simulating stocks with rapid changes.

[20] One proposal called for the creation of a California Power Authority. The CPA could make the needed investments, but simulations showed California must make a large and permanent commitment to the new agency. Another proposal called for capacity payments that would reduce the investors "revenue problem" (see Fig 2). Simulations showed that administratively set capacity payments could reduce the tendency for boom and bust.

An encouraging development in the decade following the California crisis has been the increased emphasis on the electric utilities' obligation to serve, coupled with greater commitment to integrated resource planning. An important requirement on IRPs in some areas is an upper limit on the planned fraction of generation to be purchased in the wholesale market.

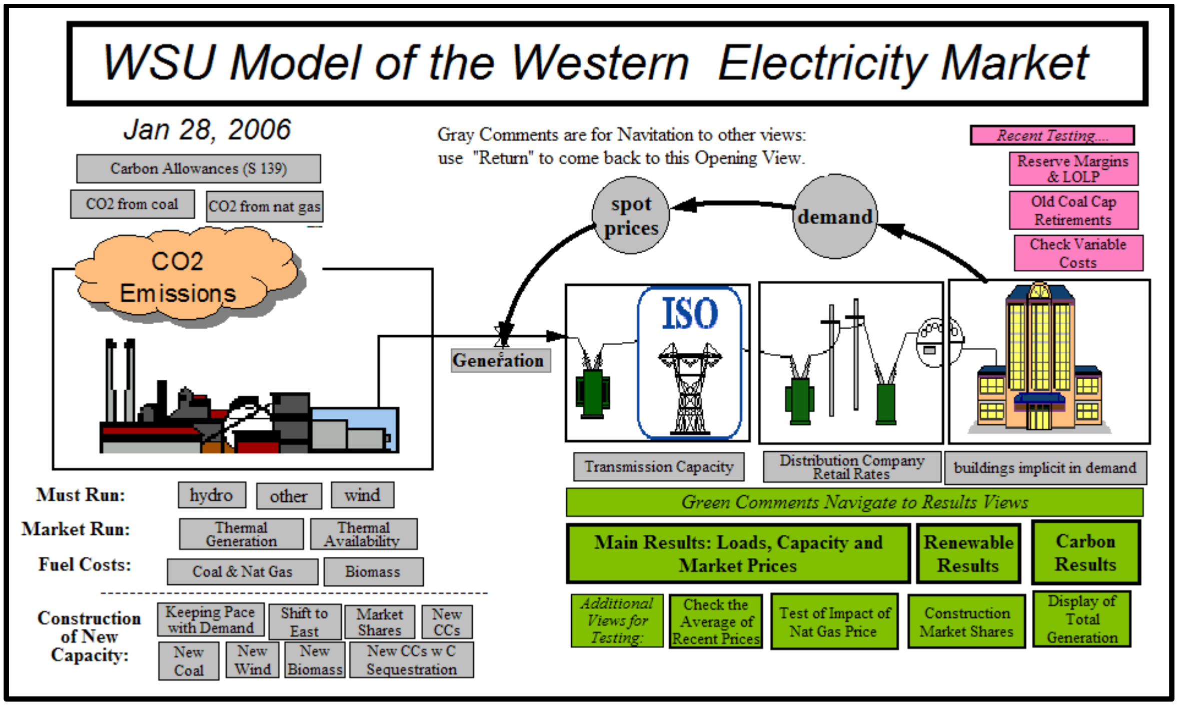

Fig 5. Opening view of the new model of the western power system.

At first glance we appear to have a choice between speed and accuracy. But this is a false impression; we can have both speed and accuracy if we replace the fast-acting stocks with algebraic equations that deliver the same results. In our situation, the fast-acting stock is clearly the spot price in Fig. 3.[21]

Guided by learning from the CEC modeling, we were able to write algebraic equations for the spot price for any hour of the day. We then wondered how does the model advance from one hour to the next in chronological time? The answer was to drop the use of chronological time and create 24-element array variables. The arrays were used to keep track of demand, generation, spot prices, CO2 emissions and other variables that change from hour to hour.

The new calendar included a typical day in each month,[22] with spreadsheets used to store 12 sets of demand load factors to start the algebraic calculations. Time was defined in months with DT set to 1 month. A 20 year simulation needed only 240 steps, so the simulations appeared instantly. A full set of 24 hourly results were not easily shown in Vensim graphs, so the results were exported to spreadsheets for display of daily dispatch graphs, like those in Figs 6A,B.

[21] The fast-acting stocks may be "high-turnover stocks" that move material quickly through the system. They can be replaced with algebraic equations to give the equilibrium values of both the stock and the associated flows. Sometimes the fast-acting stocks hide in the obscure corners of a complicated model. We can search them out by doubling the value of DT and repeating the simulations. The new simulations will eventually show inaccurate results, and the troublesome stock will reveal itself with "ringing" behavior (Ford 2010, p 227-230).

[22] One day per month was considered sufficient to create monthly average prices, revenues and CO2 emissions and other key variables needed for the study of SB 139.

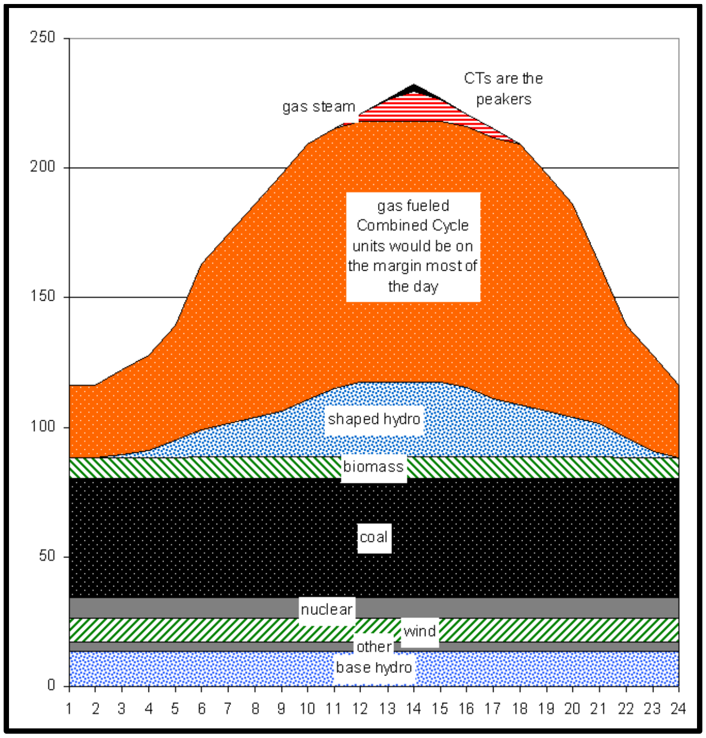

Fig. 6A. Daily dispatch on a peak day at the end of the base case simulation.

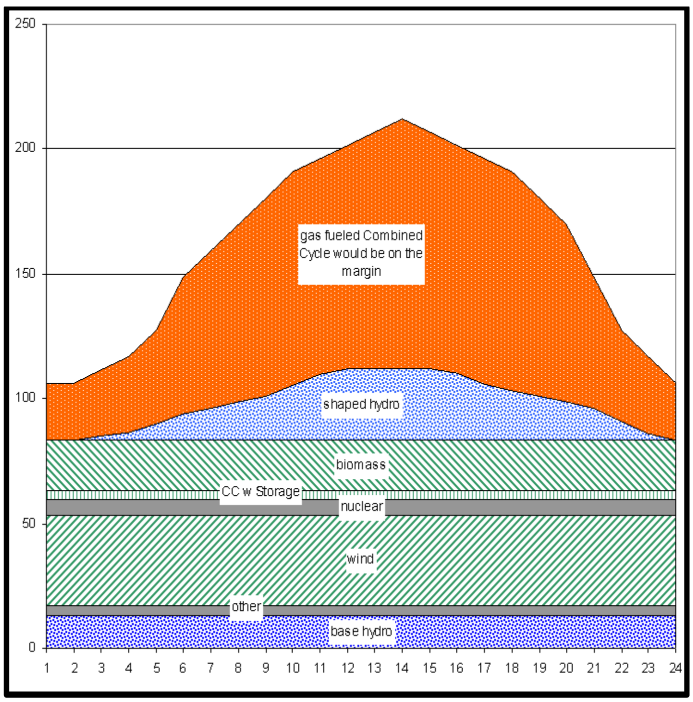

Fig. 6B. Daily dispatch on a peak day at the end of the simulation with SB 139.

Figs 7A,B show the simulated impact of SB 139 on CO2 emissions. Carbon prices were set to follow EIA estimates for the nation as a whole. The market opened at $20 (per MTCO2) in 2010 and increased to $80 by 2025. The cost of carbon allowances led to a 75% reduction in emissions by 2025, a reduction similar to EIA projections for the nation as a whole. The most dramatic effect was reduced generation from coal, starting with elimination of new coal plant construction followed by gradual reduction in the use of existing plants. SB 139 led to higher wholesale prices and a 25% increase in retail rates, a rate-payer impact half as large as the EIA expected for the nation as a whole (Ford 2008).

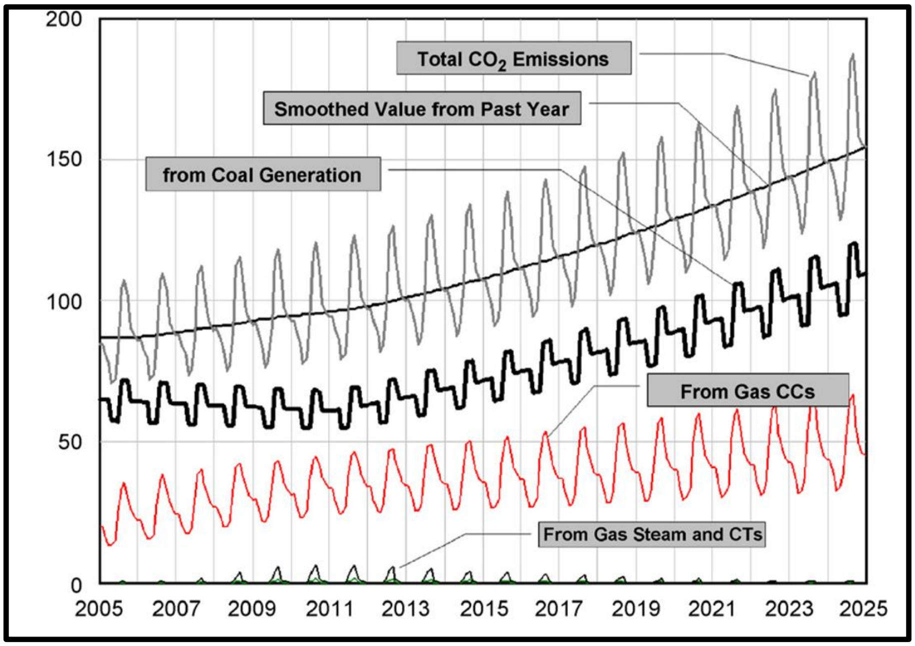

Figure 7A. CO2 emissions (MMTC/yr) in the base case simulation.

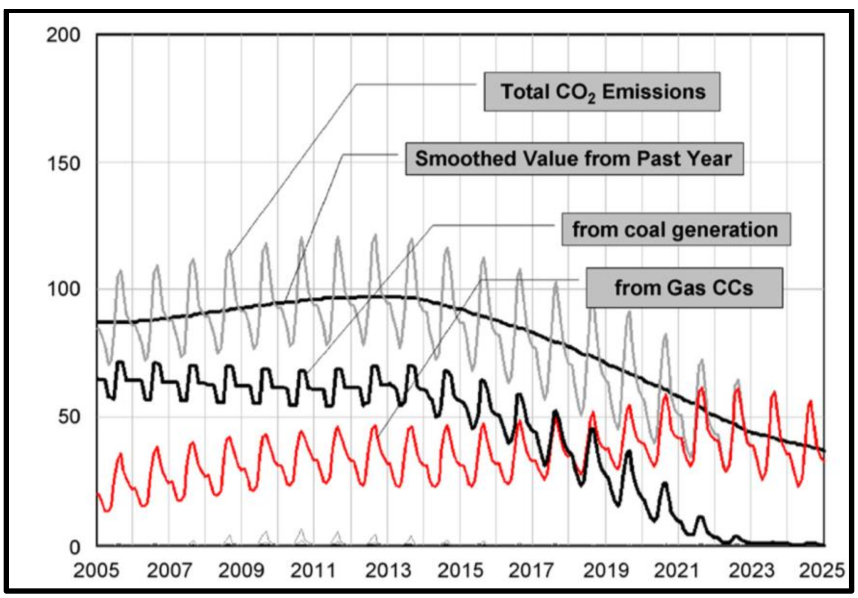

Figure 7B. CO2 emissions in the simulation with SB139.

The use of 24-elment arrays to keep track of hourly results within a long-term model was well demonstrated in the NSF study, so it was natural to apply the same approach when asked to study the long-term value of storage on the Ontario power system.

Introduction to the Ontario Power System Study

This study was initiated by NRStor, Inc. of Toronto, Ontario to simulate alternative uses of an advanced, compressed air energy storage system. The simulations showed multiple uses with estimates of monetary values to rate-payers in Ontario. Monetizing the value helped set the stage for procurement and contracting for new storage facilities, now underway in Ontario.

A full description of the model and the results is given in a 60-page White Paper (Ford 2015). This paper describes the modeling process with a focus on the methods used to simulate a mix of short-term and long-term dynamics.

The modeling process began where good system dynamics projects should begin -- with a group discussion of the reference mode. Participants were invited to sketch their own target patterns with complete freedom on the choice of the variable on the Y axis and the time units and time horizon on the X axis. This protocol led to a surprising number of target patterns,[23] and the selection of the reference mode came down to a choice between short-term and long term dynamics; specifically, should we develop a weekly model to show hourly operations of the storage facility or should we aim for a 30-year model to show monetary benefits over the life of the new facility. The group selected the long-term target pattern, and a model was designed to run from 2013 to 2043, allowing time for the storage technology to become available and operate over a 20-year lifetime.

Following the NSF method, we decided to simulate a typical day in each month, with hourly results represented in 24-element arrays.[24] The model was designed for both realism and speed, and the fast simulations were important in the team's internal discussions, even more important in the discussions with key agencies in Ontario.[25]

Fig 8 shows the opening view of the model, with navigation and sliders on the left; the main navigation buttons are shown in grey; they connect the user with the three sectors, while the words and arrows draw attention to some of the feedback loops. Peak hour generation is often used to describe power systems, so this graph appears in the opening view with peak demand climbing to 30,000 MW by 2040. Generation is shown for a typical day for each month, with must-run generation from hydro, CHP, and wind at the bottom of the stack.

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[23] The freedom of expression allowed airing of differences of opinion at the outset of the modeling process. The initial target pattern was not the first choice of some, but their views were not forgotten. Indeed, their ideas for short-term operational modeling were eventually incorporated in the modeling system.

[24] Some operational questions could be addressed by 24-element arrays. Hourly electricity loads were combined with hourly generation and loads from the storage facility for visual examination in spread sheets prior to transfer to the Vensim array variables.

[25] The power agency participants were impressed by the model, and they suggested many improvements, most of which focused on improved portrayal of the power system. The participants were equally impressed by the speed with which their suggestions were implemented. The follow-on discussions had fewer suggestions for modeling of the power system and more ideas on how to make better use of the storage facility.

Coal-generation is barely visible as a thin, black segment in the first year of the simulation.[26] Nuclear plants account for a large portion of generation in Ontario, but many of the units need refurbishment. Nuclear generation declines during the refurbishment period (2016 to 2028), and gas-fueled CCs and CTs fill in as needed. The orange peaks during this period show the need for imports to meet the peak hour demands.

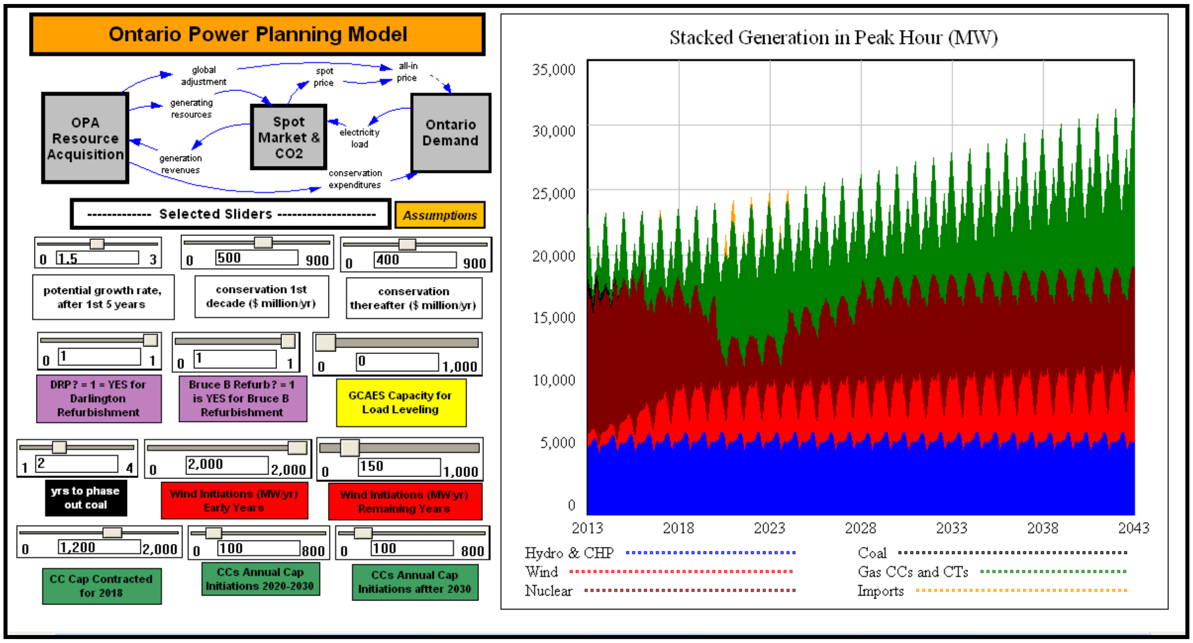

Figure 8. Opening view of the long-term planning model.

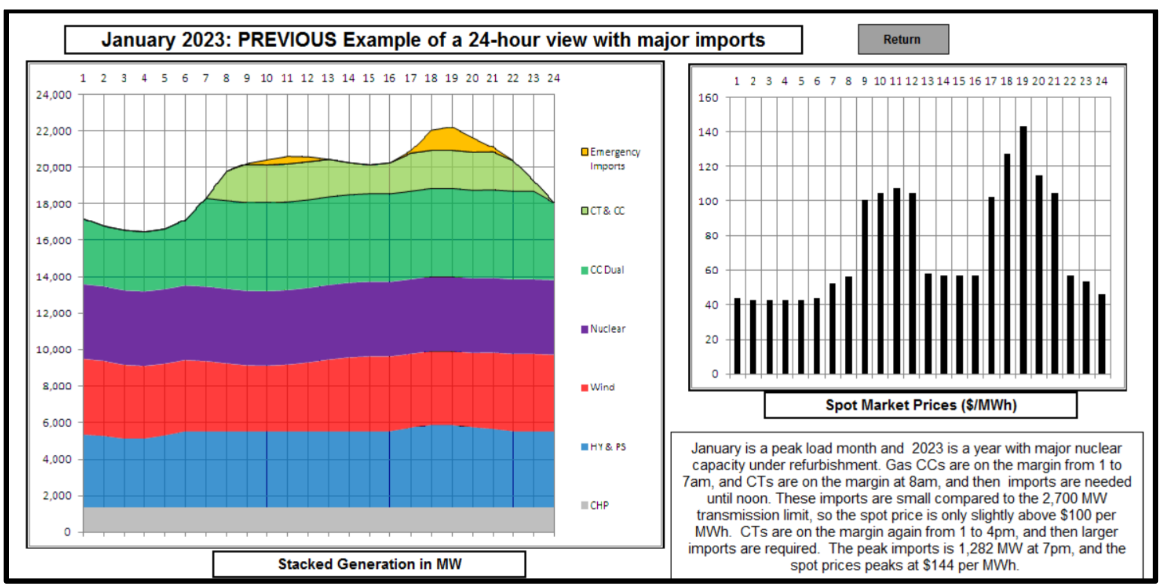

Figure 9. An example of a 24-hour dispatch, with stacked generation from CHP, main hydro, pumped storage, wind, nuclear, combined cycle, CTs and imports.

[26] Ontario has acted administratively to phase out all coal-fired generation. This bold decision led to a 90% reduction in power sector emissions in the past decade. The elimination of its coal-fired generation is said to be the single largest greenhouse gas reduction in North America (Energy 2013, p 8).

Fig 9 shows an example of daily dispatch for a day when all sources of generation were needed.[27] The left-side graph shows combined cycle, dual cycle plants on the margin in the night time hours, with spot prices around 40 $/MWh. The spot prices increase when CTs are needed, and increase further when imports are required to balance the system.

The opening view of the OPA resources sector is shown in Fig 10. Navigation to the existing resources is provided in orange; navigation to the proposed GCAES facility is provided in yellow. The results are summarized with a stacked graph of total cash flows to and from the OPA. Total annual payments to generators are on the left. They amount to around $10 billion at the start, over $16 billion by the end of the simulation. Payments to gas generators (in green) and wind generators (in red) account for most of the growth in payments.

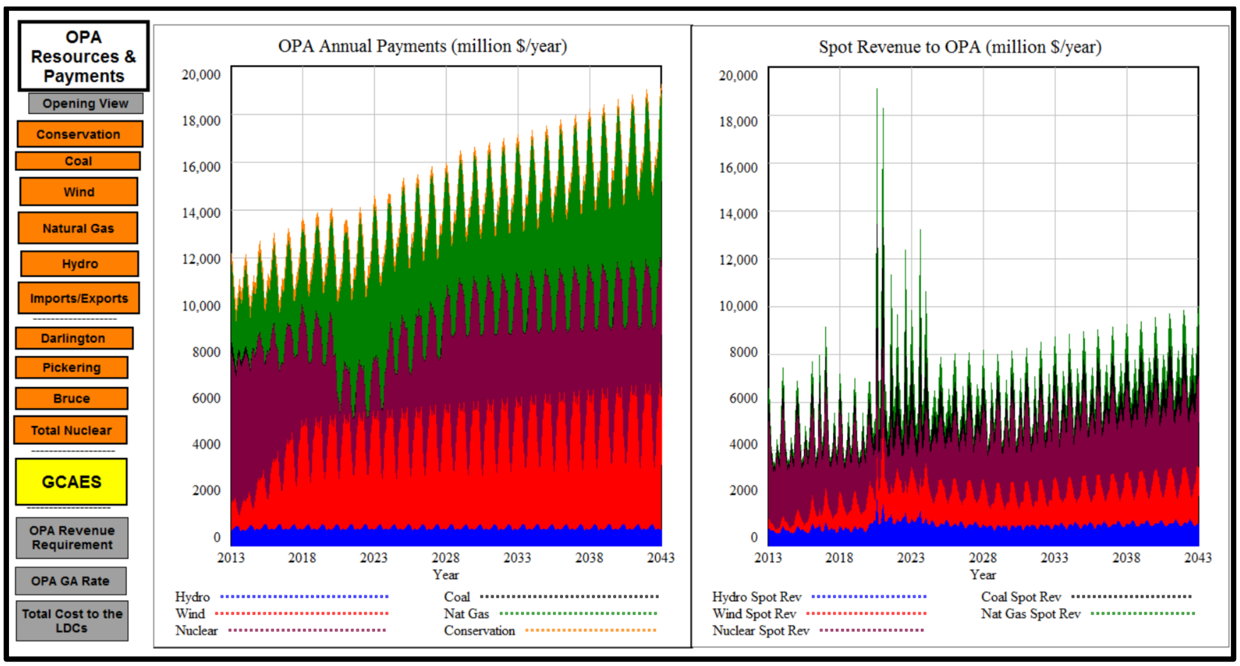

Figure 10. Opening view of OPA sector.

The spot revenue to OPA is shown on the right-side graph. This is cash flow from the generators back to the OPA.[28] The nuclear refurbishment is responsible for many changes in cash flows: lower payments to nuclear generators, higher payments to gas generators, and a small decline in total payments. Meanwhile, the right-side graph shows increased return payments due to higher spot prices in the refurbishment period. The OPA net revenue requirement is formed by subtracting the return payments (on the right) from the total payments (on the left).

[27] The results from this day were stored in 24-element arrays. These values were exported to a spreadsheet to produce the time graphs in Fig 9. Bitmap images of the graphs were created to be displayed within the long-term model using Vensim's comment tool.

[28] The return payments represent the effect of claw back clauses in the contracts with the size of the return payments based on the difference between the generators' variable costs and the spot market price.

Load Leveling Delivers Surprisingly Little Value

The main measure of performance is the total costs of power to the LDCs which pay the “all-in price” for energy from the OPA. Cumulative payments in the base case provides a benchmark cost. Cumulative costs in a simulation with storage were compared to the base case to learn the value of the storage facility. A similar method was used to learn if storage could reduce cumulative spot market costs. Load leveling in December, January and February followed by load leveling in August showed the best results: [29] cumulative spot market costs would be reduced by $968 million.[30]

Nearly $1 billion in reduced spot market costs is an encouraging finding since spot market price contributes to the All In Price. But a reduction in spot prices also lowers the generators’ return payments to the OPA; this raises the OPA’s net revenue requirement, thus increasing the All In Price to the LDCs. The return payments contracts apply to over 90% of the generation, with the percentage expected to grow over time, so we would expect only 5% to10% of the spot market benefits would reach the LDCs. The simulation confirmed this expectation: only $62 million of the $968 million benefit would reach the LDCs.

The minimal value of load leveling was shared with power agency participants in modeling demonstrations. Some were initially surprised by the low value, but they agreed that the result made sense after discussing the Ontario rules for setting the All In Price. The discussions then turned to different sources of value, with the most frequent suggestion focusing on the OPA plans for new peaking capacity. With GCAES providing 1,000 MW in the peak months, participants viewed the 1,000 MW of generators from GCAES as suitable for peaking service. We removed 1,000 MW of CTs from the expansion plan and found that load leveling/CT displacement would deliver over $2.5 billion in value to the LDCs.[31]

We then discussed the best use of storage in the other eight months of the year. With Ontario’s plans for major growth in wind generation, we turned our attention to the use of storage to provide wind integration services. This new topic presented a methodological hurdle, as the dynamics of wind integration were not amendable to the 24-element arrays approach. We needed an entirely new method, so we committed to the development of a short-term operations model which would act in concert with the long-term model.

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[29] December, January and February are the peak winter months; August is the summer month with a secondary peak. Load leveling works best in peak months because the generation in peak hours can lower peak hour spot prices by a larger margin that the increase in off-peak spot prices from the pumping loads. The simulations showed that load leveling in the other 8 months would be counter-productive for the Ontario power system.

[30] The base case assumed 65% round-trip efficiency at the GCAES facility. The pumping patterns were altered to work with efficiencies of 60%, 65% and 70%. Sensitivity testing showed that the spot market benefits varies by plus or minus 12% with changes in the round-trip efficiency

[31] The vast majority of this value came from reduced need for the OPA to make capacity payments and maintenance fee payments to the combustion turbine operators. The elimination of these plants had little impact on spot prices, so the 90% reduction associated with return revenues did not apply.

The Ontario Study Turns to a Modeling System

The new modeling system is shown in Fig 11. We retained the long-term model and added a short term model to simulate power system operations over a typical week. The main stock and flows structure is shown in Fig l2. As you might expect, the amount of energy stored in the cavern at GCAES is the main stock. The pumping flows add energy to the stock; the generating flows remove energy from the stock. The color-coded flows indicate that the storage may be used for either load leveling, wind integration or curtailment reduction.

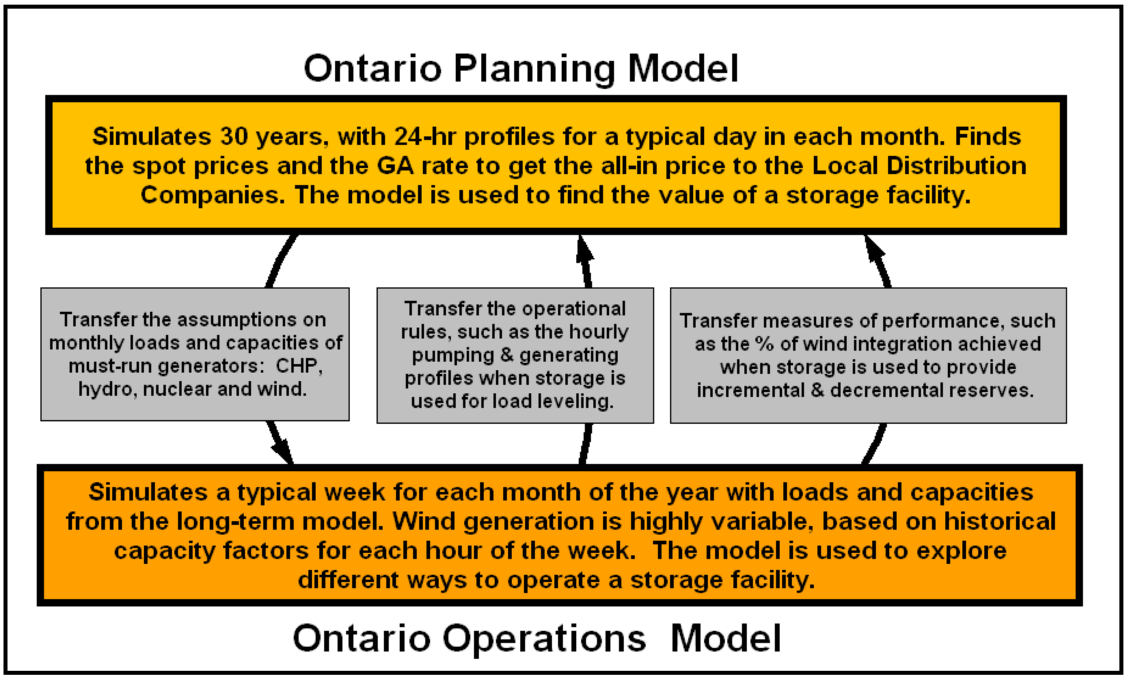

Figure 11. Design of the new modeling system.

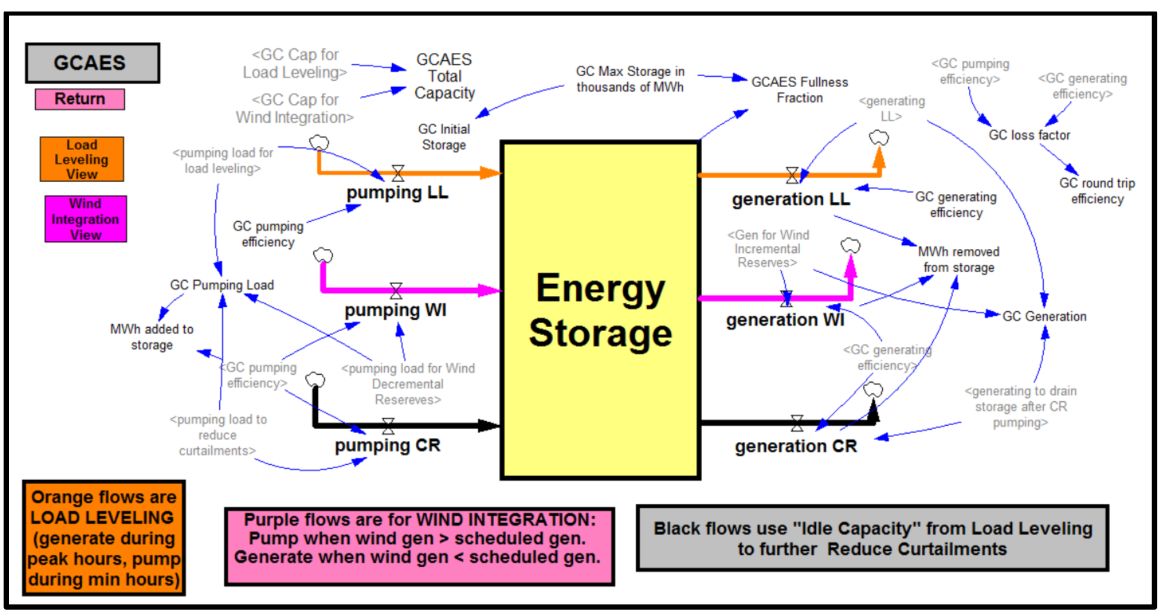

Figure 12. Stock and flows for energy storage in the short-term moddel.

Fig 13 shows the operations model with stacked generation in view. The input sliders were used to match the corresponding results for a February day in 2028. The simulations were then used to obtain aggregate measures of performance for the storage facility. The combination of models working in tandem elevated the discussions within the NRStor team and with experts from the power agencies in Ontario.

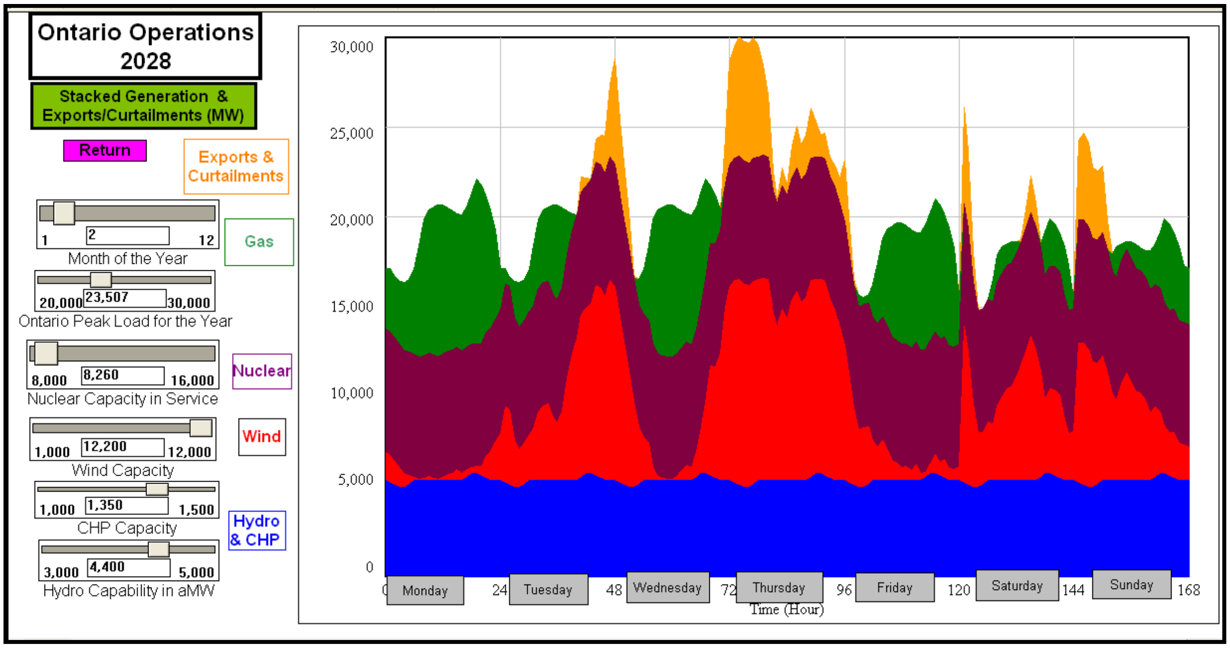

Fig 13 Simulated operations for a week[32] in February of 2028

Fig 13 shows a graph of stacked generation organized for easy comparison with Fig 8. Hydro and & CHP power generation are relatively constant at the bottom of the stack, but wind generation is entirely different. Fig 13 shows surges[33] in wind generation that lead to major changes in the stack. Nuclear plants provide constant generation throughout week, and gas fired generation meets the remaining need. Fig 13 shows that gas generation varies in the opposite direction of wind generation. Monday, for example, has lower wind generation, but higher gas generation.

The high wind generation on Thursday creates the most dramatic situation: gas generation is completely eliminated; total generation exceeds Ontario loads, and the extra generation can be exported to neighboring regions. However, if potential exports exceed the transmission export capacity, Ontario will be forced to issue curtailment orders to must run, must pay generators.[34]

[32] A week long simulation was selected as energy storage scenarios were often examined over a typical week.

[33] Wind generation is based on historical generation factors. A rapid increase in generation followed shortly by a rapid decline is common. This pattern may be caused by a large wind storm moving through the region.

[34] Curtailments were a problem when we began the model development, so we were encouraged to explore the use of storage to reduce curtailments. This can be achieved by running the pumps when curtailments are imminent, and releasing the stored energy later in the week when generation would displace gas generation. As for the Thursday situation in Fig 13, the potential exports are 6,000 MW, but the transmission capacity is only 2,700 MW. Ontario could sell 2,700 MW and the be forced to issue curtailment orders for 3,300 MW.

Using Storage to Provide Wind Integration

Wind generation is a key part of Ontario's effort to develop clean energy and a green economy. The base case simulation sets wind initiations to achieve Ontario's clean capacity goal of 10,700 MW by 2018, as explained in Table 1. Wind integration involves how the power system operator deals with the uncertainty in the generation from wind turbines. System operators require forecasts of future wind generation, and forecasts are used to schedule flexible generation to meet the net load, the load remaining after subtracting the forecasted generation.

Wind Assumptions in the Long Term Model		
Model Variable	Value	Comments
Initial Capacity	2,700 MW	Wind capacity will grow to 10,700 MW
Capacity Construction Delay	12 months	which meets the goal for clean capacity
Capacity Initiations first 4 years	2,000 MW/yr	(Solar or bio capacity are not included)
Capacity Initiations thereafter	150 MW/yr	Additional capacity initiations are needed
		to limit the the rebound in CO2 emissions
Capacity Factors in Long Term Model		
Annual Average	29.25%	ORTECH analysis of the IESO hourly
Monthly Variations	May - Sept: below average	wind generator output
	Nov - March: above average	
Hourly Variations	average around 6pm	
	5-6% higher during off-peak	
	9% lower around 10am	
Wind Assumptions in the Operations Models		
Capacity (MW)	same as Long Term model	value entered manually with a slider
Capacity Factors	historical hourly values	
Proxy for Scheduled Wind	1 hour forecasting lag	The forecasted wind is 1 hr late. This
		assumption gives good inc-dec results.
Inc-Dec Sensitivity Factor	1.00	no need to use the sensitivity factor
Geographic Diversity?	0	no, we use the historical values

Table 1. Wind assumptions, exactly as they appear within the long-term model.[35]

Forecasting errors are inevitable, so the system operator needs reserves to ensure that generation matches demand. When the actual generation is lower than forecasted, the operator needs additional generation to compensate for the error. This need is called incremental reserves. When actual generation exceeds the forecast, the system operator needs increased load (or reduced generation) to compensate for the error. This need is called decremental reserves. The combined need is abbreviated in this paper as INC & DEC.

[35]Navigation to the tabular summary of assumptions begins with the link to "assumptions" in Fig 4. The assumptions view provides navigation links to eight tabular summaries of different parts of the model. These embedded summaries helped us keep track of our own assumptions, and they made for better discussions with the participants in power agency briefings.

Fig 14 shows the operations model results for a simulation with a 1,000 MW GCAES devoted to wind integration in May of 2028. Actual generation was based on historical capacity factors applied to12,200 MW of wind capacity. This simple scaling makes sense if the new wind farms are located in the same wind regions as the existing wind farms.[36] Scheduled generation is shown in red. Data on scheduled generation (or forecasted generation) were not available in Ontario, so we created a proxy for scheduled generation based on a system dynamics analysis of wind integration in the Pacific Northwest (Llewellyn 2011).[37]

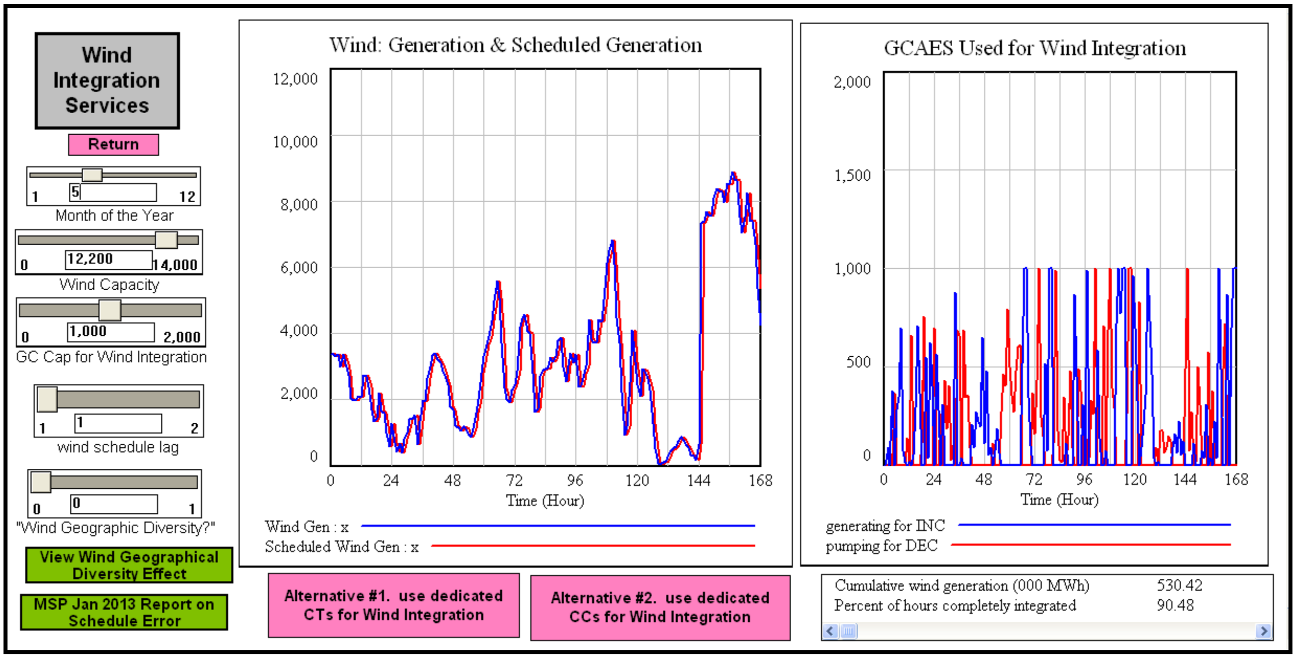

Fig 14. Results from application of 1,000 MW of GCAES to wind integration.

[36] The geographic diversity slider at the bottom of Fig 14 changes the pattern of wind generation to represent a more dispersed location of wind farms. This slider was used very seldom, as most participants found simple scaling either easier to understand or more descriptive of future wind generation.

[37] Scheduled generation is the same as forecasted wind generation, but there were no data sets on forecasted generation in Ontario. Interviews with experts suggested that forecasts are surprisingly accurate, but large errors can occur simply by misjudging when the wind storms will move through the region

Lewellyn (2011) used system dynamics to simulate operation of the pumped storage facility at Banks Lake adjacent to the Columbia River. His model measured time in minutes, with 10,800 minutes for the week-long simulation. Five minute capacity factors were used for wind generation, and wind forecasts were based on a 60-minute persistence. We expanded his model to represent proxy forecasts that would come close but leave the region with significant errors if the wind storms did not arrive as expected.

Proxy forecasts were examined by comparing the resulting INC & DEC with the actual INC & DEC in Llewellyn's model. The best proxy was a forecasted generation with a 60 minute, first order exponential delay of the actual generation. This proxy provided a realistic INC & DEC pattern, and the errors could be viewed as what would happen if a wind storm arrived in the region one hour earlier than expected.

The differences between the red and blue curves is the INC & DEC requirement. The right-side graph shows the simulated operation of GCAES to provide these reserves, with generation in blue and pumping in red. A quick glance at the right-side graph shows that the generators and pumps are operating below capacity early in the week, so we know that all of the INC & DEC is provided early in the week. But more rapid changes in generation later in the week led to greater demands for both INC and DEC. The GCAES facility attempts to meet these needs, but it is limited by 1,000 MW of capacity. The table in the lower-right corner reports the cumulative results: GACES provides 100% of the reserves needed in 90% of the hours in the week.

The operations model was used to explore wind integration for all months of the year. When simulating April, for example, the percentage of hours fully integrated falls to 87%. In August, a month with less wind, 94% of the hours are fully integrated. The weighted average results for the entire year were recorded for scenarios with different levels of wind capacity and different sized storage facilities. These results provide the nonlinear performance curves needed to simulate the value of wind integration in the long-term model (as noted in Fig 11). The long-term model was then used to accumulate the MWh of wind integration provided over the life of the GCAES facility.

Another Data Obstacle: What is the $/MWh Value of Wind Integration?

Provision of wind integration comes at a cost, with the $/MWh cost expected to be low when the system has modest wind capacity and plenty of flexible capacity. For this reason, or perhaps for other reasons, data on the $/MWh cost of providing wind integration was not available from power agencies in Ontario. This final data obstacle appeared to block the way toward our goal of estimating the monetary value of the GCAES storage facility. Lacking Ontario reports on the $/MWh value, we turned to reports in the USA for perspective.[38]

A common finding from these studies is that the cost of wind integration will grow with growth in the installed wind capacity. As wind capacity increases, the power system operator grows increasingly anxious about running out of flexible capacity. As still more wind capacity is installed, the power system will need to build new, dedicated facilities to provide the integration.[39] A common suggestion is for gas burning plants dedicated to wind integration so their cost can serve as an upper limit on the likely cost of wind integration.

[38] Electric utilities in the USA often estimate the $/MWh cost of wind integration as part of the integrated resource planning (IRP) process or in separate wind integration studies. A useful review of these estimates was provided by the Lawrence Berkeley National Laboratory (LBNL 2005).

[39]This general idea is discussed in the *Northwest Wind Integration Action Plan.* It describes a wind integration supply curve, a conceptual curve with starting and ending points similar to Fig 15. Their supply curve begins with a zero point based on our reasoning for Ontario. Their supply curve increases with higher levels of wind capacity, eventually reaching an upper limit based on the fact that "some analysts suggest that there is an upper limit on how high wind integration costs can go based on the cost of gas-fired resources." (NPPC 2007).

Fig 15 shows our best estimate of the wind integration value curve.[40] The value grows to $15 per MWh as the installed capacity grows to 15,000 MW. The general shape of the curve reflects the conclusions from wind integration studies, with the curve's position anchored by the three points highlighted in Fig 15.

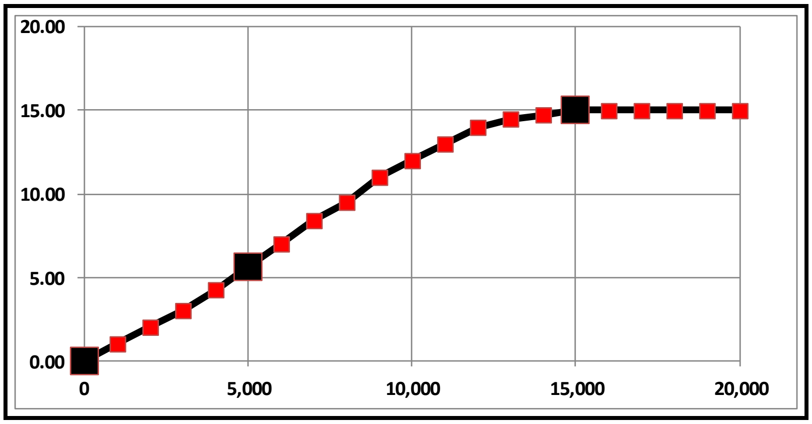

Fig 15. Best estimate of a value curve for the value of wind integration services (in $/MWh) with wind capacity in Ontario (in MW) on the horizontal axis.

The first point shows zero cost for the first increment of wind capacity, as the power system will have some idle, flexible generating capacity which can be put to use to provide a small amount of wind integration. The second point is just over $5 per MWh when installed capacity reaches 5,000 MW. This estimate is typical of many IRPs and wind integration studies (LBNL 2005) and similar to the wind integration rate at the BPA.[41]

The third point in Fig 15 is more difficult to discern from existing studies since they dealt with lower levels of wind capacity. So we estimated the asymptotic limit based on our own analysis of a block of CTs or CCs used for wind integration. The weekly model showed these gas-fired generators could provide the equivalent services available from a 1,000 MW GCAES. A surprising result for some was the need for 2,000 MW of gas-fired plants with 50% of the capacity operating as a set point.[42] The cost of wind integration was estimated at $15 per MWh regardless of whether CTs or CCs were dedicated to wind integration.

[40] The "value curve" is used to estimate the value of GCAES providing wind integration in Ontario. However, it may also be called a "cost curve" since it is obtained by reviewing cost estimates from wind integration studies.

[41] The second point was located at $5.60 per MWh to show BPA's published wind services rate. Their example is relevant to Ontario because both the BPA and the OPA have significant hydro resources, and both envision substantial growth in wind generation. Furthermore, managers in both systems are anxious about the lack of sufficient flexibility and concerned about curtailments.

[42] Gas generation would remain at 1,000 MW if there was no need for INC and DEC. Generation would increase above the set point if INC was needed and decline below the set point when DEC was needed.

The value curve in Fig 15 was the subject of intense discussions in the briefings with the power agencies. Some participants thought the curve over-estimated the cost of achieving wind integration with existing resources. Others expressed concern that Ontario was already reaching limits on the use of its flexible capacity. Given the wide range of opinions, we created low, medium and high versions of the value curve with a slider to allow sensitivity analysis on the importance of this controversial curve.

The Monetary Value of Storage to Ontario Rate-Payers

Fig 16 shows the values of the multi use facility with low, medium and high value curves for wind integration. The value of wind integration is shown in black, stacked on top of the $2.5 billion value from load leveling/CT displacement discussed previously. Cases 3 & 4 were selected from 6 cases with different plans for expanding wind capacity (Ford 2015, p 38).

Case 4 was a commonly discussed situation in the middle of the study since it used Ontario's original plan for achieving the 10,700 MW clean energy goal by 2018. The combined values ranged from $6.5 billion to a high of $8.7 billion.

Case 3 was viewed by many as the most likely case at the end of the study since it adjusted the wind capacity due to the OPA announcement of delaying achievement of the 10,700 MW goal until 2021. The combined values in this case ranged from $6.1 billion to $8.4 billion. This meant less wind capacity and less value from using GCAES for wind integration.

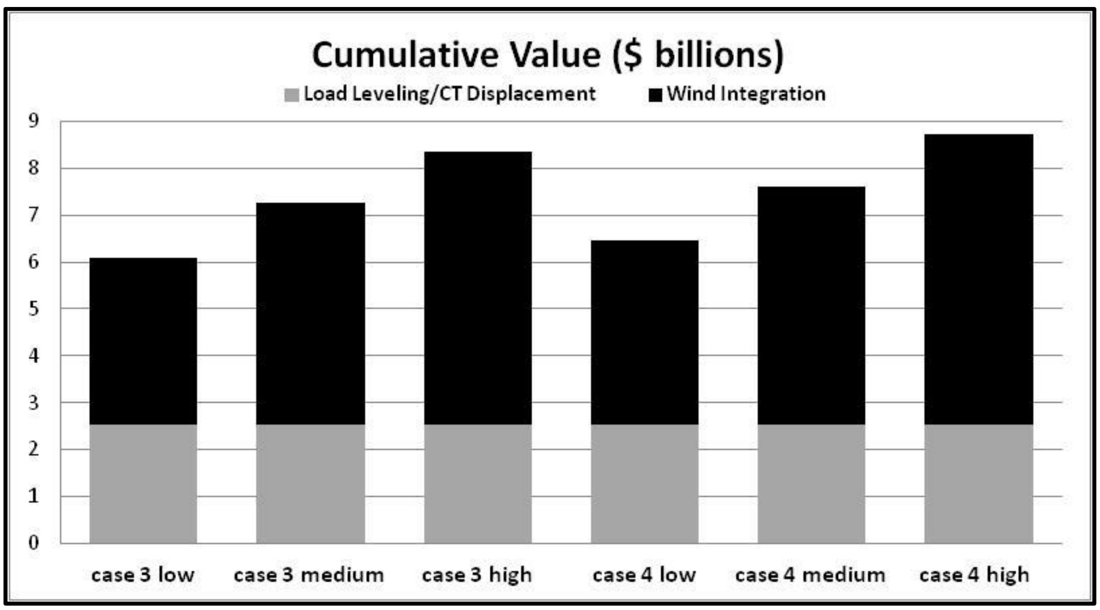

Figure 16. The cumulative value of a 1,000 MW multi-use facility with different cases for wind capacity and with different versions of the value curve in Fig. 15.

Fig 16 provides the type of results envisioned at the outset of the study. Substantial values to the LDCs are simulated with a systems-oriented model presented in open meetings with full discussion with power agency participants. The sensitivity testing showed that substantial values remain under a wide range of assumptions. This monetizing of storage value helped set the stage for procurement and contracting for new storage-facilities in Ontario.

Methodological Conclusions

The methods described in this paper were developed for improved simulations of policy questions involving a mix of fast-acting and slowly developing dynamics in the power industry. Electric power has its own unique features, but the need to better understand both short-term and long-term dynamics is not unique to the energy sector. It can arise in many different systems, and many readers will have faced the challenge of simulating a mix of short-term and long-term trends.[43] This paper concludes by summarizing one method from the each of the case studies that worked well for us and could work well for others.

- The study of the California energy crisis arrived at a slow-running model with an awkward calendar. This method is not recommended for others. Nevertheless, the study proved quite useful despite the sluggish simulations with only four typical days per year. An important reason for the success was the effort to match historical behavior in long-run construction and in short-term spot prices, both factual and counterfactual. The match with historical construction in Fig 1 and the match with historical prices in Fig 4 helped build confidence with participants despite the 2-3 minute simulations and the awkward calendar.

- The NSF study simulated long-term dynamics associated with the change in investments due to carbon prices proposed in S139. Short-term operations were represented with array variables with 24 elements, one for each hour of the day. The key to this approach is the ability to discard the rapidly changing stocks (like the spot price stock in Fig 3 that slowed the simulations in the CEC study.) The short-term equilibrium values of the rapidly changing stocks are represented with algebraic equations that produce the same result.[44]

- The most promising method for simulating mixed dynamics is the development of a pair of models with the insights from the short-term model used to create performance curves for the long-term model, as depicted in Fig 11. This method was developed in the second half of the Ontario power system study, and it enabled the simulation of wind integration which accounted for the majority of the value of the proposed storage facility. The two models in the Ontario modeling system operate within their own time horizons, with clear displays as shown in Fig 8 for the long-term and in Fig 13 for the short term.

[43] The article by Homer (1999) illustrates with a combination of "macro and micro" models. The micro model simulated daily queuing and assignment dynamics to support the long-term simultion of field services for a major producer of equipment for semiconductor manufacturing. Homer described the micro modeling as a time consuming affair, one that was worth the effort as it led to increased confidence in the findings from the macro model.

[44] Examples for human population and the global water cycle models are provided by Ford (2010, p. 227-230).

Transferability of Results

The coordinated use of two models in the Ontario study is a generic approach which could be adopted by researchers and consultants working in a wide range of systems. The transferability is illustrated by our own work on National Parks. Researchers at WSU have been interested in National Park planning and management, and we have completed an initial study for planners at Glacier National Park. Fig 17 shows our vision of an integrated modeling system similar to the modeling system used in the Ontario power study.

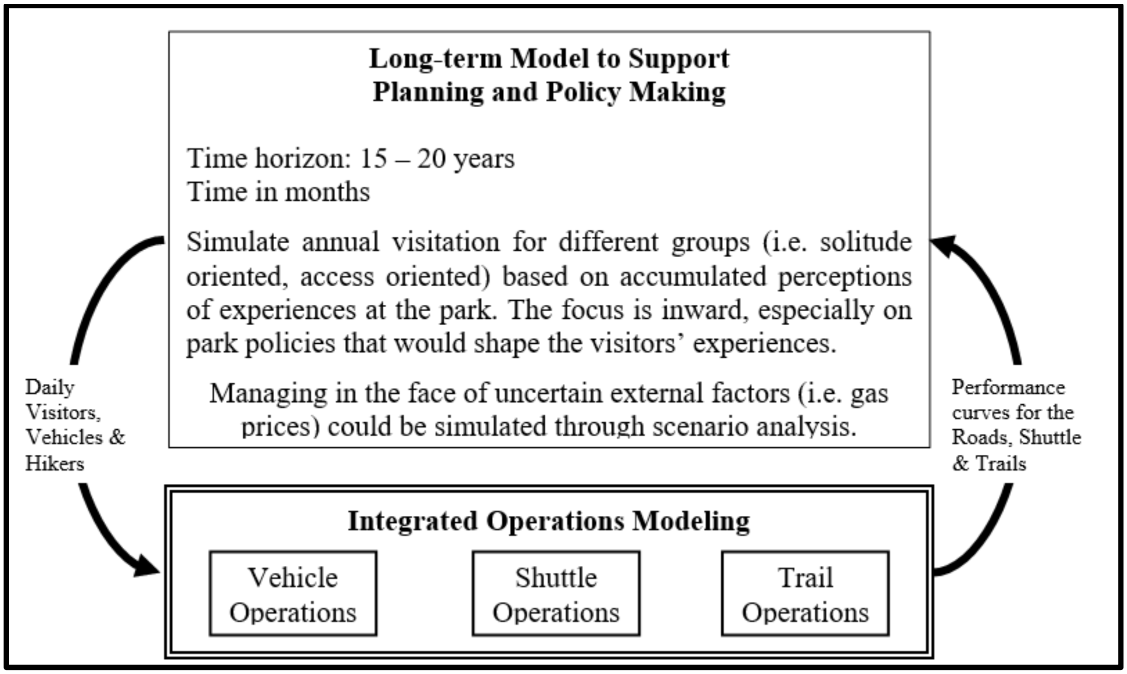

Figure 17. An integrated system for modeling support of National Park planning.

This diagram envisions a coordinated use of a long-term model and a short-term model to support National Park planning. The operations model simulates vehicles, shuttle buses and hikers for a typical day in the summer season, with inputs on visitors and vehicles provided from a long-term model. Results from the operational model could be converted to performance curves needed in the long-term model. This concept is explained in a conference paper (Ford, Nguyen and Beall 2012) with illustrative results from the operations model developed for Glacier National Park (Nguyen 2012).

At first glance, one might view the Ontario Power System and Glacier National Park as having nothing in common. But after some reflection, many would agree that both systems are well suited to simulation with the system dynamics approach, and that planners in both systems are concerned about long-term dynamics, short-term dynamics and their interactions. When readers view their own systems in this manner, they may pursue the coordinated development of two models. Hopefully, they will find the approach as useful for them as it was for us in the Ontario power system study.

Acronyms, Abbreviations and Units

AB 1890	Assembly Bill 1890 in the California Legislature, August 1996
BPA	Bonneville Power Administration
CEC	California Energy Commission
CHP	Combined Heat and Power electricity generation
DT	DT is short for Delta Time, the time step in the numerical simulation
GCAES	General Compression Advanced compressed air Energy Storage
INC & DEC	Incremental and decremental reserves associated with wind integration
IRP	Integrated Resource Planning
ISO	Independent System Operator (in California)
LDCs	Local electricity Distribution Companies (in Ontario)
MMTC	Million Metric Tons of Carbon equivalent emissions
MW	Megawatt (a measure of electric power or electric capacity)
MWh	Megawatt-hour (a measure of electric energy)
NSF	National Science Foundation
OPA	Ontario Power Authority
SB 139	Senate Bill 139, the Climate Stewardship Act of 2003
WSU	Washington State University

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