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Analysis of Foresight in Long-Term Energy System Models

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Abstract

Foresight assumptions are central to long-term electric sector planning and energy systems models. These model features can alter investments and shape policy analysis. With a particular focus on intertemporal perfect foresight and sequential myopic approaches, this investigation analytically and numerically assesses the conceptual and computational implications of model foresight assumptions. Results of the investigation include a mathematical outlining of the mechanism of divergence between model outputs with different foresight assumptions, development of a validated sequential myopic mode for EPRI's REGEN model, and associated numeric insights. The investigation concludes with recommendations for REGEN and long-term energy models more broadly, including a preliminary exploration of systematic combination of foresight approaches.

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PRIMARY AUDIENCE: Electric company staff and analysts engaged in developing and applying long-term energy system models for resource planning, technology assessment, and policy analysis.

SECONDARY AUDIENCE: Consumers of model outputs and other stakeholders who want to understand how assumptions about foresight can influence assessments.

KEY RESEARCH QUESTION

Foresight assumptions are central to long-term electric sector planning and energy systems models, potentially altering investments and shaping policy analysis. However, implications of foresight assumptions for model outputs and tradeoffs in how they are represented are less clear.

RESEARCH OVERVIEW

With a particular focus on intertemporal perfect foresight and sequential myopic approaches, this investigation analytically and numerically assesses the conceptual and computational implications of model foresight assumptions. Results of the investigation include a mathematical outlining of the mechanism of divergence between model outputs with different foresight assumptions, development of a validated sequential myopic mode for EPRI's REGEN model, and associated numeric insights.

KEY FINDINGS

- A divergence in valuation of capital-intensive technologies under an intertemporal perfect foresight approach relative to a sequential myopic approach stems from a different distribution of costs and revenues over time for these technologies relative to competing options. Such differences would not be picked up by the sequential myopic approach and its constant annualization factor (Section 3).
- An alternate foresight approach ("sequential limited foresight") solves the model in sequential myopic mode but with some foresight information included, based on an intertemporal solve. To harness any computational benefits associated with the sequential approach, the intertemporal model could solve at lower resolution, not including energy storage for example, and then a more computationally detailed sequential approach would include more detail (Section 4).
- Under certain circumstances, model outputs may not differ greatly across approaches, while in others, specific technologies may be disadvantaged in a sequential myopic approach relative to an intertemporal perfect foresight approach (Section 5).

WHY THIS MATTERS

Foresight assumptions can have a marked effect on model outputs, and yet may be embedded in technical details with less salience than technology and policy assumptions in the use of long-term energy models. This research provides recommendations for model development and interpretation in light of different foresight approaches for long-term electric sector and energy systems models.

HOW TO APPLY RESULTS

The analytic model in Section 3 provides general insights about different foresight approaches. However, numerical findings in Section 5 are conditional on scenario-specific assumptions and regions of analysis.

LEARNING AND ENGAGEMENT OPPORTUNITIES

EPRI members and others who are interested in learning more about EPRI research into long-term planning and modeling should refer to the following research programs:

- Resource Planning for Electric Power Systems (Program 178)
- Energy, Environmental, and Climate Policy Analysis (Program 201)

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PROGRAM: 201

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Section 1: Introduction: Analysis of Foresight

Foresight assumptions are central to long-term electric sector planning and energy systems models. These model development decisions can alter investments and shape policy analysis, making them of interest to planners and policymakers to understand the implications of deep decarbonization and high renewables scenarios. This investigation aims to elucidate the implications of foresight assumptions for the outputs of these models.

To accurately characterize system investments and operations, especially for variable renewables and energy storage, forward-looking scenarios may require additional temporal and spatial detail than currently represented in many long-term planning models, presenting a computational challenge. Foresight approaches with shorter time horizons can have fewer variables to keep track of over time, potentially providing a solution to this computational challenge. However, a shorter model foresight horizon may introduce a conceptual challenge, by failing to represent relevant intertemporal dynamics for these scenarios. This motivates this investigation into the conceptual and computational tradeoffs of foresight representation in long-term energy models.

This investigation focuses on the sequential myopic foresight approach, and what it gains and loses relative to the intertemporal approach. The latter approach is currently employed by EPRI's Regional Economy, Greenhouse Gas, and Energy (REGEN) [1] model [1], which we use for numeric analysis in this investigation. Figure 1-1 introduces the concepts of intertemporal foresight and sequential myopic foresight, the primary subjects of this investigation. A model with intertemporal foresight solves all operation and capacity decisions simultaneously, while a model with sequential myopic foresight sequentially solves for each individual time period. Under a decarbonization scenario with the intertemporal approach for example, the model can make its early investment decisions knowing there is a steep carbon price in the future, while with the sequential myopic approach, investment decisions in early time periods would have no knowledge of this carbon price increase.

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[1] REGEN features regional disaggregation and technological detail of the power sector and linkages to other economic sectors. This state-of-the-art model has been used in many analyses and peer-reviewed articles (https://esca.epri.com/models.html)

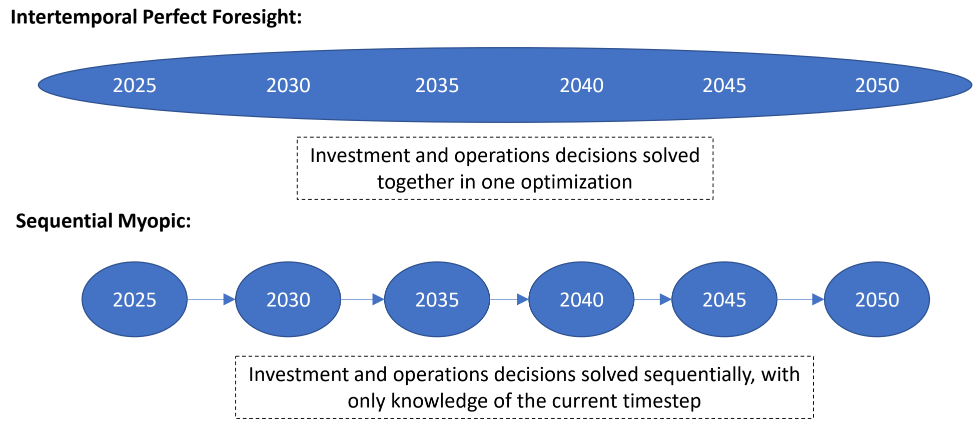

Figure 1-1
Intertemporal and sequential myopic approaches

Note there are, in some sense, two modeling dimensions presented in Figure 1-1, a) sequential / intertemporal, and b) myopic / perfect foresight. That is, a model can be solved in sequential mode with a greater degree of foresight than myopic foresight, and similarly, an intertemporal model can be solved without perfect foresight, but with explicit modeling of uncertain future parameters. These distinctions will be discussed in Section 2.

To conduct this analysis of foresight in long-term energy models, Section 2 provides background and a literature review, Section 3 compares the mathematical structure of intertemporal and sequential myopic approaches, Section 4 outlines the code development to EPRI's REGEN model to incorporate a sequential myopic mode, and Section 5 presents associated numeric analysis.

Results from this investigation include a context in which to place modeling choices around foresight, a mathematical outlining of the mechanism of divergence between intertemporal model outputs and sequential myopic outputs, validated sequential myopic REGEN code and associated insights, including the analysis of a limited foresight sequential mode. From these results, the investigation concludes with an outlining of actionable next steps for the REGEN model, and long-term energy models in general. As will be shown, foresight assumptions can have a marked effect on model outputs, and yet may be embedded in technical details with less salience than technology and policy assumptions in the use of long-term energy models. This investigation should contribute to the community of model developers and users who want to understand how assumptions about foresight can influence model-based assessments.

Section 2: Background

Foresight is a central assumption to planning models in all domains, as it shapes the model solution landscape. In this section, we discuss foresight at a broad contextual level followed by an overview of related energy modeling literature.

Context

Descriptive models of foresight in human and biological decision systems may provide some guidance on how to represent foresight in normative models such as long-term electric sector planning and energy systems models. Of particular interest is when decisions taken with only local information could lead to aggregate decisions "as if" there was full global knowledge, for example if agents following simple rules with no apparent foresight produce outcomes leading to the perception of foresight to the external observer. This dynamic underlies economic insights from Adam Smith to Arrow and Debreu. Similarly, we learn from Wolfram [2] how simple rules can lead to arbitrary complex structures, while the free energy principle [3] shows "as if" behavior at many scales in natural systems through local responses to local information. Furthermore, the key enabler of tractable solution of convex optimization problems is that this type of problem admits algorithms where local updates based on local information can be guaranteed to reach a global optimum.

While such examples may indicate that models with local foresight only could model how real systems work, they also indicate that a normative model that models the "as if" behavior directly may also be able to capture the essential dynamics of a system and the decision-making options facing it. In this spirit, EPRI's REGEN model, for example, adopts a perfect foresight intertemporal optimization approach. This approach allows exploration of questions such as decarbonization of the power system, where multi-decade investment decisions are explicitly traded off against cumulative short-term operational decisions and associated costs.

Trutnevyte [4] places the outputs of optimization models in context, stating that the optimization approach can help decision makers through a "bounding analysis" of possibilities, as optimization model solutions geometrically occur, by definition, where constraints intersect. A suite of solutions, generated through scenario analysis for example, can bound the space of solutions, potentially providing insight to model consumers. This argument may be extended to foresight approaches, with intertemporal optimization bounding the solution space to intertemporal questions, whereas a sequential myopic solution has no such optimality guarantee to an intertemporal question.

Referring to Figure 1-1 above, we note that a model may be solved with intertemporal perfect foresight or sequential myopic foresight assumptions, and still have the exact same parameter assumptions, for example solar power costs in 2040. In this sense, the sequential myopic approach is also a perfect information approach, just that the horizon has been curtailed at each sequential step. This highlights that alongside the foresight horizon assumptions at a decision step, what information is assumed at that timestep is an important consideration. An alternate to perfect foresight assumptions is the broad literature[2] on stochastic optimization. Stochastic optimization approaches can be set up to be sequential (potentially with explicit learning at each step) or solve an intertemporal problem across uncertain parameters.[3]

With this context underlying approaches to modeling foresight, we next consider literature that analyzes the consequence of different foresight assumptions on model outputs, specifically between the two foresight modes displayed in Figure 1-1, intertemporal perfect foresight and sequential myopic.

Consequences of Foresight Assumptions

That the foresight assumption is material to model outputs is shown in a multi-model comparison study by Misconel et al. [8], where foresight assumptions were shown to be a primary driver of differences across model outputs. This study considered shorter time horizon questions than in this study, however a similar importance of foresight was shown in the long-term MESSAGE model by Keppo and Strubegger [9]. Keppo and Strubegger also discuss the technological consequences of a sequential limited foresight assumption relative to intertemporal foresight, with "lagging investments" in earlier model periods leading to higher investment requirements in later model periods, along with more reliance on fossil fuels for the scenarios analyzed.

Babrowski et al. [10] show one of the motivating factors for imple menting a sequential myopic approach, reporting a 10x reduction in computing time to solve a long-term optimization model of the German power system when solved in sequential myopic mode instead of intertemporal mode. Similarly, Thomsen et al. [11] show a "significantly reduced" run time in sequential myopic mode, while noting that for some technologies with high upfront costs, the sequential myopic approach cannot compute the benefits over time, leading to underinvestment relative to the intertemporal model. Both papers deem the change in model

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[2] For example, Powell [5] states that there are "over 15 distinct communities that work in the general area of sequential decisions and information." For an overview of stochastic programming methods for the electricity capacity planning problem, see Bistline & Weyant [6].

[3] The concept of sequential decision making under uncertainty, where there is often an explicit learning stage at each timestep, is particularly worth mentioning, as it useful to make a distinction with the deterministic sequential myopic approach discussed in this document. See Kann & Weyant [7] for a discussion of sequential decision making under uncertainty in energy/economic policy models.

outputs with this approach to be acceptable for the scenarios at hand, and mention that there are sets of input parameters where there is not a large difference in output between the foresight approaches.

While we have discussed in this section the differences in model outcomes between foresight approaches, both Nerini et al. [12] and Heuberger et al. [13] integrate these modeling differences into policy implications, stating how myopic strategies in the real world could increase the cost of electric sector decarbonization. Of relevance to the analysis in Sections 4 and 5 below, Nerini et al. state the benefits of using intertemporal and sequential myopic foresight approaches in tandem.

In the numerical analyses below, we see that there are findings that certain technologies may be disadvantaged in a sequential myopic approach, but also that under certain circumstances, model outputs may not differ greatly across approaches. These are numeric findings, conditional on the scenario specific assumptions. We next outline the general mechanism for these effects in the optimization model structure, before using the mechanism as a validation check on our own numerical analysis, and as a guide to using the foresight approaches in parallel.

Section 3: Analytic Investigation

In this section, we analytically investigate the difference between solving a long-term energy model with intertemporal foresight or sequential myopic foresight. Examples in the literature we have discussed make this comparison numerically, with the comparisons then contingent on specific parameterizations. The analytical approach can guide us to mechanisms driving the difference, from which we can inform our implementation and use of a sequential myopic approach.

The model analytically outlined here is based on EPRI's REGEN model in the essence of vintaging and time steps, essentials for foresight analysis. For clarity, the analytical model does not include other REGEN features not central to this foresight analysis including multiple regions, transmission, and retrofit technologies.

Table 3-1, Table 3-2, and Table 3-3 introduce the sets, variables, and parameters in our analytical model.

Table 3-1
List of sets

Set	Description
$t \in 0,1,2,\dots,T$	Time steps (model years)
$v \in 0,1,2,\dots,V$	Vintage of generation capacity
$s \in 0,1,2,\dots,S$	Dispatch periods (e.g. hours)
$g \in 0,1,2,\dots,G$	Generation technology

Table 3-2
List of variables

Vector variables	Description
$x_{v,t} \in \mathbb{R}_+^{S\times G}$	Electricity generation
$z_{v,t} \in \mathbb{R}_+^{G}$	Generation capacity
$y_t \in \mathbb{R}_+^{G}$	Generation investment

Table 3-3
List of parameters

Parameter	Description
$c_x \in \mathbb{R}_+^{S \times G}$	Generation cost
$c_z \in \mathbb{R}_+^{G}$	Capacity (O&M) cost
$c_y \in \mathbb{R}_+^{G}$	Investment cost
$a \in \mathbb{R}_+^{G \times S}$	Generator availability
$d_t \in \mathbb{R}_+^{S}$	Electricity demand

Each timestep *t* of the sequential myopic approach may be represented as the following optimization:

$$
\begin{aligned}
&\textit{minimize}\ \ (c_x x_t + c_z z_t + c_y y_t) && && \textit{Eq. 3-1}\\
&\textit{subject to}\ \ \textstyle\sum_v x_{\{v,t\}} \geq d_t && && :\lambda_t\\
&\qquad x_{\{v,t\}} \leq a z_{\{v,t\}} && \forall\, v && :\rho_t\\
&\qquad z_{v,t} = y_t && \forall\, v = t && :\gamma_t\\
&\qquad z_{v,t} \leq \kappa_{v,t} && \forall\, v < t && :\delta_{v,t}
\end{aligned}
$$

Where $\kappa_{v,t}$ is a parameter representing the capacity, $z_{v,t-1}$ solved for in the previous period of the sequential solve, and λ, ρ, γ, and δ are the vectors of dual variables associated with their respective constraints.[4]

Then in the intertemporal setting, *x*, *z*, and *y* are solved across all time periods simultaneously.

$$
\begin{aligned}
&\textit{minimize}\ \ \textstyle\sum_t (c_x x_t + c_z z_t + c_y y_t) && && \textit{Eq. 3-2}\\
&\textit{subject to}\ \ \textstyle\sum_v x_{\{v,t\}} \geq d_t && \forall\, t && :\lambda_t\\
&\qquad x_{\{v,t\}} \leq a z_{\{v,t\}} && \forall\, v,t && :\rho_t\\
&\qquad z_{v,t} = y_t && \forall\, t = v && :\gamma_t\\
&\qquad z_{v,t+1} \leq z_{v,t} && \forall\, v,t && :\delta_{v,t}
\end{aligned}
$$

After introducing both models, we next assess when they will produce equivalent outputs. Analyzing the optimality conditions of the intertemporal model, we obtain the following identity that is active when some positive investment is made in a technology:

[4] Note that the sequential myopic approach may be interpreted as the first iteration of an instantiation of an Alternating Direction Method of Multipliers (ADMM) approach to solving the intertemporal problem. Solving the problem with ADMM is discussed in [14].

$$c_y = \sum_s \rho_s + \delta_{\{v,t\}} \qquad \textit{Eq. 3-3}$$

This can be interpreted that marginal costs (left-hand side) must equal marginal benefits (right-hand side). The first marginal benefit term is the current-timestep net revenues and the second term is future revenues (how much the new capacity is "sold" to the future for).

The analogous optimality condition in the sequential myopic formulation is as follows:

$$c_y = \sum_s \rho_s \qquad \textit{Eq. 3-4}$$

That is, the investment is only made if current net revenues can match the investment cost of the new capacity. This clearly is an unrealistically high hurdle for an electricity generation investment, so sequential models are set up such that the investment cost is annualized. A typical annualization factor, for example, is in the range of 5%-10% (Eq. 4-1).

It follows that we may set up a sequential myopic model to match the output of an intertemporal model if we do not annualize the costs but adjust the investment costs by the δ dual variable vectors returned from the solved intertemporal optimization model, leading to an implicit technology-specific annualization factor, dependent on future conditions, rather than the default same rate applied to each technology. Equivalently, there could be a parameterization of an intertemporal model where the solution is such that the implicit annualization factor for each technology is identical.

We may relate this analytic finding to the numeric findings observed in the literature, both for the case where the sequential myopic approach matches the output of an intertemporal model for a set of "stable" input parameters and for the case where they diverge. We can see how a divergence in valuation of capital-intensive technologies for example stems from a different distribution of costs and revenues over time for these technologies relative to competing technologies, and this would not be picked up by the sequential myopic approach and its constant annualization factor.

This analysis is focused on new investments, but the same logic and analogous optimality conditions may be shown for capacity retirement decisions. While there is no investment cost to annualize in this case, it is still true that sequential myopic models do not see any future net revenues from a unit that an intertemporal model would see, and thus may, at the margin, be relatively over-enthusiastic to retire units. The magnitude of this effect relative to the changes in current year valuations of capacity due to the changes in the investment mix outlined above is a numerical matter. We now turn to our numerical investigation, which the analytical principles outlined here guide.

Section 4: Code Development and Validation

This section describes the code development and validation under this investigation. As previously mentioned, EPRI's REGEN model employs an intertemporal foresight approach, and the code developed under this investigation enables the model to be alternately solved with a sequential myopic foresight approach.

Development

A sequential myopic mode for the REGEN model was developed in collaboration with EPRI staff.[5] The implemented sequential myopic mode aligns with the analytic representation introduced in Section 3. Implementation of the sequential myopic mode involved code changes around all intertemporal model constraints. In Section 3, our analysis included a core intertemporal constraint on generation capacity, while in the REGEN model intertemporal constraints are also present on existing capacity retirements and investments in transmission, retrofit technologies, electricity storage, and hydrogen infrastructure.

As discussed in Section 3, in sequential myopic mode, to tradeoff long-term investments with operational costs and considerations, an annualization factor is applied to investment costs. The annualization factor f for a generation technology of lifetime l with a discount rate r, we calculate as follows:[6]

$$f = \frac{r}{1-(1+r)^{-l}}$$

Eq. 4-1

With this identity, f goes to r as l goes to infinity, implying that for a technology with a long lifetime, investment costs are annualized by simply multiplying by the discount rate, while for shorter lifetime technologies, the annualization factor increases, increasing the investment costs in a given sequential model year for that technology. For example, assuming a discount rate of 5%, a technology with

[5] The intertemporal REGEN model is coded in the GAMS modeling language. Sequential myopic mode was implemented such that a switch enabled REGEN be solved in either foresight mode.

[6] Eq. 4-1 follows the formulation for annualization factor used in the static mode of the REGEN model outlined in Section 2.7 of [1].

a 50-year lifetime has an annualization factor of 5.4%, while a technology with a 25-year lifetime has an annualization factor of 7.1%. While this technology-specific feature allows for some difference in payback duration when in a sequential myopic mode, it remains that technologies with the same lifetime will have the same annualization factor despite potential difference in the distribution over time of costs and revenues across different scenarios.

Validation

To validate the implementation, Equation 3-3, and the associated analytic guarantee of when a sequential myopic solve would match an intertemporal solve, was harnessed. Information from an intertemporal solve essentially enables the provision of technology-specific and scenario-specific annualization factors, encoding information about the future. When the model is run in sequential myopic mode with this information, and it returns the same outputs as the intertemporal solve, we have a validation check against coding errors in the implementation of sequential myopic mode.[7]

Sequential Limited Foresight

This validation exercise suggests an alternate foresight approach for REGEN, where the model is solved in sequential myopic mode but with some foresight information included, based on an intertemporal solve. To harness any computational benefits associated with the sequential approach, the intertemporal model could solve at lower resolution, not including energy storage for example, and then a more computationally detailed sequential approach would include storage as an option. This could be considered a "sequential limited foresight mode." While there is no guarantee of a global intertemporal optimum with this adoption of mixed resolutions, there is also none with default myopic assumptions earlier discussed.

We next discuss numeric implications of the sequential implementations across selected REGEN model scenarios.

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[7] In practice, a combination of numerical issues and the presence of knife-edge solutions prevented this validation being fully realized in all scenarios with the REGEN model, but all deviations were small in terms of objective function value and model technology choice.

Section 5: Selected Numeric Insights

This section compares model outputs across both intertemporal and sequential myopic foresight modes. The comparisons illustrate the implications of the analysis in previous sections within the numerical grounding of the aforementioned[8] state-of-the-art REGEN model.

We then harness the computational benefits of the sequential myopic approach to run REGEN at hourly resolution, maintaining chronology between dispatch periods and facilitating the inclusion of energy storage technologies.[9] These computational benefits are discussed alongside any conceptual tradeoffs.

Comparison of Numerical Results

Figure 5-1 and Figure 5-2 present model outputs for a reference scenario with current state and federal policies and incentives (e.g., tax credits, portfolio standards) but no federal carbon pricing. In this illustrative example, the most important aspect is not the absolute values presented in Figure 5-1 and Figure 5-2 or the exact nature of the scenario, but the insights based on difference between the figures. We see in sequential myopic mode, relative to intertemporal mode, that there is less wind generation, more gas generation, and no decline in nuclear generation.

[8] See Footnote 1.

[9] See Merrick et al. [14] for analysis of storage representation and associated computational challenges.

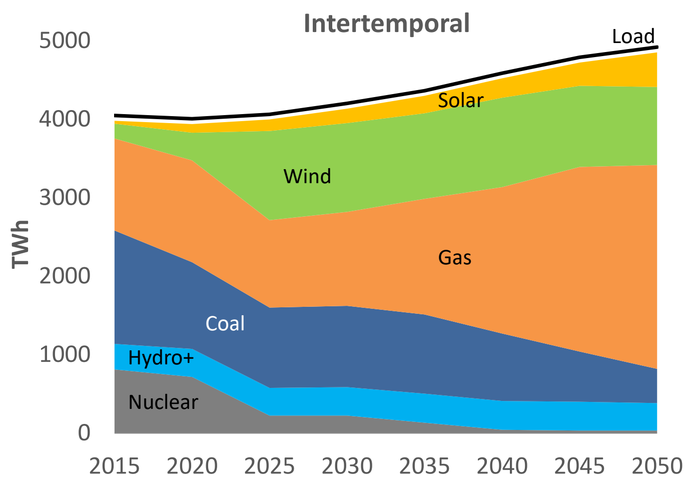

Figure 5-1
Generation, no carbon price scenario, intertemporal foresight

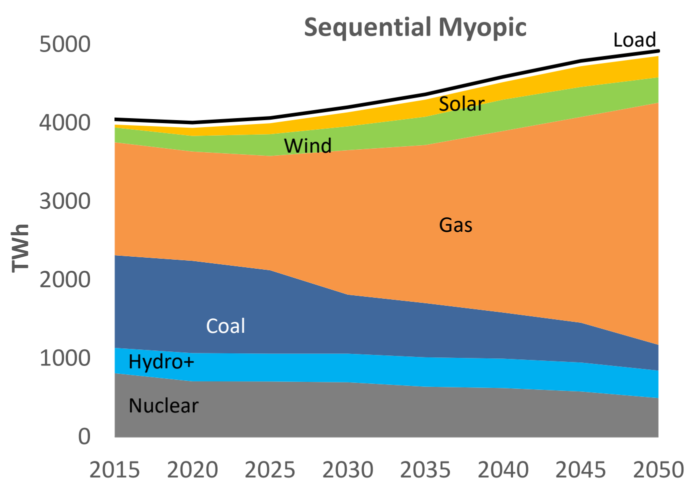

Figure 5-2
Generation, no carbon price scenario, sequential myopic foresight

This result is driven primarily by new wind investment in the 2025 model year under intertemporal foresight. We may state from our previous analysis that the mechanism underlying differences between the two figures is that, in the sequential myopic case, wind investment is relatively undervalued. If it was valued appropriately, its presence would crowd out the generation from existing gas and nuclear assets we see in the sequential myopic case relative to the intertemporal case.[10]

[10] Sequential myopic mode has a representation of future revenues from new investments and no representation of future revenues from existing capacity. When existing capacity is retained in this mode at the expense of new investment, we then know it is through relative undervaluation of the new investment, and not overvaluation of existing capacity.

As outlined in Section 3, we may use the dual of the intertemporal solution to extract what implicit annualization factor would be required for sequential myopic model outputs to match intertemporal model outputs. In this example, for model year 2025, we may calculate an implicit annualization factor of 7.6% from the intertemporal case, a decline from the 8.6% factor employed by default in this sequential myopic instance. In this intertemporal solution, the distribution of benefits to wind are more heavily weighted in the future than that implied by the default annualization factor. While there are numerous moving parts that determine model outcomes, with different technology options and associated annualization factors interacting, this result aligns with the earlier statement that the default sequential myopic mode was missing a portion of the future benefits of wind power. Also, it is worth noting that the relatively small change in annualization factor indicates that the two technology outcomes of Figure 5-1 and Figure 5-2 have similar overall costs (i.e., a "flat" optimal solution).

Concluding this comparison and confirming a motivation for the sequential myopic approach in the literature, Table 5-1 shows computational requirements for the respective foresight modes for these REGEN model scenarios.

Table 5-1
Computation comparison

	Intertemporal	Sequential Myopic
Running time (laptop)	32 minutes	12 minutes
Peak Memory	885 MB	229 MB

Figure 5-3 and Figure 5-4 compare foresight modes for a carbon price scenario. The carbon price trajectory is displayed in Table 5-2.

Table 5-2
Carbon price scenario ($ per metric ton)

2025	2030	2035	2040	2045	2050
7	100	140	197	276	387

One might expect in this scenario, with a rising carbon price, that there could be a substantial difference in model outcomes in earlier model periods under sequential myopic foresight. However, in contrast to our previous comparison, there is less noticeable difference in generation outcomes across Figure 5-3 and Figure 5-4.

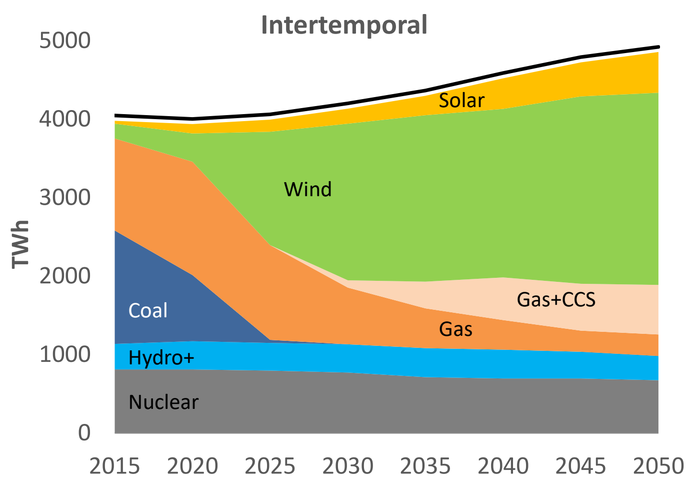

Figure 5-3
Generation, a carbon price scenario, intertemporal foresight

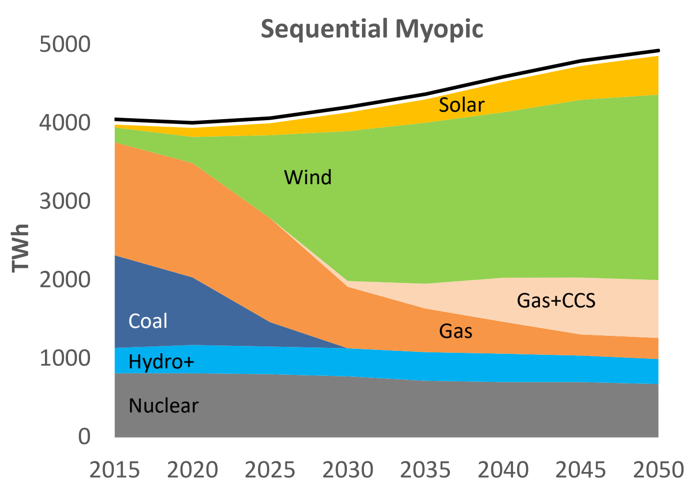

Figure 5-4
Generation, a carbon price scenario, sequential myopic foresight

For this scenario, the myopic decisions in response to the carbon price in each period better align with the intertemporal decisions. For example, the implicit annualization factor for wind power in 2025 from the dual of the intertemporal solution is 8% in this scenario, closer to the sequential myopic default annualization factor.[11]

However, on closer inspection of the 2025 model year, we may observe the myopic effects through lower retirement of coal generation, and lower deployment of wind, relative to the intertemporal scenario. Figure 5-5 presents a

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[11] That there happens to be a lower distribution of future net revenues for wind power (per unit capacity) in this case despite rising carbon prices shows the difficulty of knowing *a priori* whether sequential myopic mode will match intertemporal mode.

time slice through the 2025 model year for our two comparisons. Myopic foresight can mean a delay in investments and retirements relative to an intertemporal optimum.

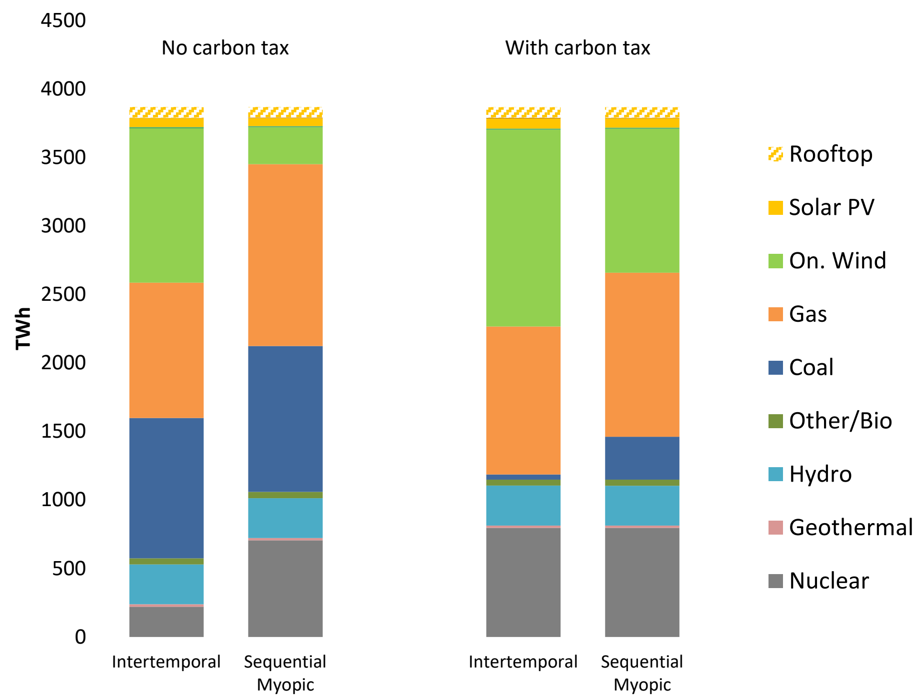

Figure 5-5
Generation by technology in 2025 under different foresight approaches

These numerical comparisons show a broad pattern aligned with the literature, where a model with sequential myopic foresight can underinvest or delay investment relative to intertemporal foresight, especially in technologies where value could change over time. While we focus on the primal model solution here, particularly aggregate generation, this observed underinvestment and delayed investment across scenarios leads to increased aggregate cost and subsequently dual solution prices. We also see the reduced computational time that is referenced in other papers in the literature, and a case where the sequential myopic approach, depending on the perspective and the question asked, produces similar outcomes to the intertemporal approach. There are also likely scenario definitions where the divergence would have been greater than what we report.

In contrast to the literature, we show analytically the mechanism of divergence across foresight approaches, and show that, due to the many moving parts involved in a numeric computation, it is challenging to state *a priori* in what cases sequential myopic foresight will match intertemporal foresight.

Enabling Hourly Resolution

Table 5-1 displays one of the motivations of the sequential myopic approach, namely, the lower computational burden. We harness this computational benefit to run REGEN at hourly resolution, maintaining chronology between dispatch periods and facilitating the inclusion of energy storage technologies.

Note that the computational cost of an increase in model resolution from the standard REGEN resolution of 120 “representative” periods [1] to 8,760 hourly modeling is compounded by the inclusion of variables tracking the state of energy storage in each dispatch period in each model year. We currently cannot solve the intertemporal version of REGEN at this scale, so no direct comparison of the sequential myopic approach is possible. We only may work from the principles established earlier in this report in assessing associated model outputs.

Table 5-3 shows a running time of greater than 32 hours when REGEN is run at hourly resolution in sequential myopic mode with storage included (on a desktop machine). There is a marked increase in solution time for the later model periods as REGEN keeps track of technology vintages, which accumulate over time.[12]

Table 5-3
Sequential myopic solution time (hours) at hourly resolution (with storage)

2025	2030	2035	2040	2045	2050
0.9	1.1	5.8	8.3	7.5	8.9

While the computational benefits of the sequential myopic approach enable solving REGEN at hourly resolution with energy storage included, this is likely an unacceptable run time relative to roughly 0.5 hours or less with 120 representative hours (Table 5-1). With tuning of the model implementation and the CPLEX solver, this run time is very likely possible to improve. However, this first attempt indicates the computational challenge of solving a model with the regional breadth and technological detail of REGEN at hourly resolution, even in a sequential myopic mode.

Finally, we note that the sequential myopic version of REGEN at hourly resolution may be solved with the default annualization factors earlier discussed, or with annualization factors derived from a lower resolution intertemporal run, what we term “sequential limited foresight.” This will have the same computational cost as shown in Table 5-3, plus the additional computational cost of the lower resolution intertemporal run. The adjusted annualization factors counter the delayed and reduced investment in new generation observed with the sequential myopic approach, however, have no guarantee of guiding the proposed sequential limited foresight approach to an intertemporal optimum.

[12] Long-term energy models that do not keep track of technology vintages experience faster sequential myopic solution times, with similar solution times for each model timestep.

Section 6: Conclusion

The representation of foresight in long-term energy models, while at one level, is quite a technical and functional matter, at another level, is core to the philosophical underpinnings of what a model is doing and what questions it is attempting to answer. The EPRI REGEN model has been developed on the premise that an intertemporal foresight approach aligns well with the questions it was designed to answer. This analysis has thus investigated how the move to a sequential myopic foresight approach from an intertemporal approach would change model outcomes, and the scale of computational benefit achievable in return. The consequences of the analysis extend beyond REGEN to any long-term energy models of this type.

To conduct this investigation, this analysis has reviewed relevant literature on the topic, outlined the mechanism of divergence between foresight modes analytically, implemented a sequential myopic mode for the REGEN model, and conducted numeric analysis.

In our analysis, the computational benefit of the sequential myopic approach was apparent. However, at an hourly resolution, facilitating the modeling of energy storage in the REGEN model, the computational burden was still significant. At that resolution, we cannot directly assess how sequential myopic foresight affects model outcomes relative to intertemporal foresight. At resolutions where we may compare outcomes, the divergence in model outcomes varied by scenario, is challenging to predict *a priori*, and has a significance that depends on the lens through which it is viewed.

Underinvestment, and delayed investment, in technologies where a greater fraction of net revenues occurs in future model years than implicitly expected by standard annualization factors are a feature of the sequential myopic solutions. Applying technology specific annualization factors derived from a lower resolution intertemporal model is a novel option we introduce to offset this, but there is no guarantee that this approach would bias the model's solution less than default annualization factors across all scenarios. Similarly, it is a question of judgment whether changes in model outcomes introduced by a sequential approach are more grievous than not accurately representing energy storage technologies in an intertemporal approach.

Finally, directions for future research following this investigation include:

- An improvement in computation time for the sequential myopic approach at hourly resolution, particularly for models like the EPRI REGEN model that track technology vintaging.
- Computational and conceptual research to include storage representation at the scale of the EPRI REGEN model in intertemporal mode, particularly if intertemporal foresight is the preferred modeling approach philosophically.
- An understanding of how to adjust the framing of model results if a sequential approach is adopted, given what has been shown here and elsewhere on how it affects model outcomes.

Section 7: References

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