# Chapter 2
# Modeling and Simulation in Service of Energy Policy: The Challenges

People would rather believe than know
—Edward O. Wilson

Modeling and simulation have long and well served the actors and various decision makers in the domain of energy policy. Various modeling approaches and models have been applied to address a variety of energy policy related issues. However, the journey continues. This chapter provides an overview of these modeling approaches and models identifying their key challenges in the face of emerging issues. The identified energy policy modeling related issues include the characterization of energy systems as complex dynamic systems with numerous uncertainties, nonlinearities, time lags, and intertwined feedback loops.

## 2.1 Energy Systems Modeling and Its Challenges

By and large the modeling and simulation community has successfully used a variety of methods and techniques to serve energy policy needs. For instance,

- *Linear programming and dynamic programing:* to perform capacity expansion and energy-economy analysis [e.g., WASP model (Foel 1985), MARKAL model (Fishbone and Abilock 1981), and RES model (Howells et al. 2011)]
- *Mixed-integer linear program*: to optimize distributed energy resource system [e.g., MILP model (Omu et al. 2013)]
- *Econometric methods:* to produce annual energy outlook and the role of carbon capture and storage [NEMS model (Kydes and Shah 1997) and SGM model (Praetorius and Schumacher 2009)]
- *Partial equilibrium model*: to develop the US Climate Action Plan [e.g., IDEAS model (Wood and Geinzer 1997)]
- *Optimization*: to analyze energy–economy interactions and optimize the options for $SO_2$ control (e.g., Meier and Mubayi's (1983) model and Islas and Grande's (2007) model)



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- *Scenario analysis*: to analyze energy policies (e.g., Munasinghe and Meier's (1993) model
- *Agent-based modeling*: to provide quantitative support for climate policy formulation and evaluation [e.g., ENGAGE model (Wang et al. 2013)]

have been applied to address various energy policy related issues, be it in a developing or a developed region or country. Despite the demonstrated applicability and success of these operational methods over the past several decades (Dyner and Larsen 2001), emerging issues related to the energy industry (e.g., widespread deregulated electricity markets and industry, climate change and environmental concerns, multiple stakeholders, and technological disruptions) require new capabilities of modeling methods to fully capture the dynamics of energy systems. These energy system modeling[1] challenges include modeling the existence of uncertainties (e.g., fuel prices), time delays (e.g., power plant construction time lags), nonlinear causal relationships (e.g., between changes in electricity price and its industrial use), and interacting feedback loops (e.g., additional production capacity brings in more revenue for the firm, which, in turn, leads to increased production capacity) in any energy system.

### *2.1.1 Uncertainties Abound*

In general, widespread deregulation and privatization in the energy sector of the economies has created opportunities as well as challenges for private investors including independent power producers (IPPs). In the case of developing and emerging nations including India, China, and Brazil, growing demand and consumption of energy create imbalances providing further impetus for energy sector investments (IEA 2012). However, the dynamics of the much desired stock of "investments" in the energy sector are uncertain:

i. *The nature and life of incentives and rules keep changing*. Although the learning aspects of these changes are desired, the resulting often costly, lengthy, and uncertain litigations deter potential new investments in the energy sector of the host country (e.g., Eberhard and Gratwick 2007).
ii. *Technological disruptions can severely impact investments*. Costly retrofitting or installation of new technologies, say for monitoring and control of electricity production related environmental emissions is becoming common and is highly unpredictable.
iii. *The availability and prices of fuels are rarely in smooth order*. This creates operational and financial difficulties for the energy projects.

[1]The basic premise of modeling a system is that we are able to identify the forces (i.e., components or structures of a system) behind the problematic behavior of this system (e.g., the supply of electricity lags or leads the demand). By controlling/managing the underlying structures of a system, the problematic behavior can be improved.

iv. *Deregulation has expanded the nature and dimensions of stakeholders*. Compared with the almost monopolized status of regulated regimes, now multiple stakeholders including competitors, regulators, traders, large institutional investors, shareholders, local communities, end-users, and environment lobbyists are involved in energy sector investments. Not only are they "many more" but these stakeholders often come with conflicting objectives, making energy policy decisions even more complex.

v. *Perceptions of people change and sometimes in relatively short order*. For instance, after the Fukushima nuclear accident in Japan in 2011, Germany and Switzerland decided relatively quickly to close their nuclear power plants (Larsen and Arrango 2013). Granted that the unpredictability of such external events is known, the ability of decision makers to conceive and explore such scenarios can better prepare them to deal with such uncertainties (Wang et al. 2013).

## *2.1.2 Existence of Nonlinear Relationships Is a Reality*

In energy systems, there exist nonlinear relationships between variables of the system that can hardly be analyzed with traditional econometric methods and linear programming techniques. For instance, when the price of electricity decreases, its industrial usage can see some growth (as is shown in Fig. 2.1). However, after a while, when even the price continues to fall, industrial usage of electricity will saturate (e.g., because the production reaches its maximum capacity). Likewise, the relationship between an operator's overtime work and her productivity is nonlinear; in the beginning, her productivity can increase (e.g., due to learning) but if she continues to overwork for long then her productivity will fall or even complete collapse, the *burn-out phenomenon*, can occur. Productivity gained by experienced power plant operators rarely follows a proportional path: more experience leads to

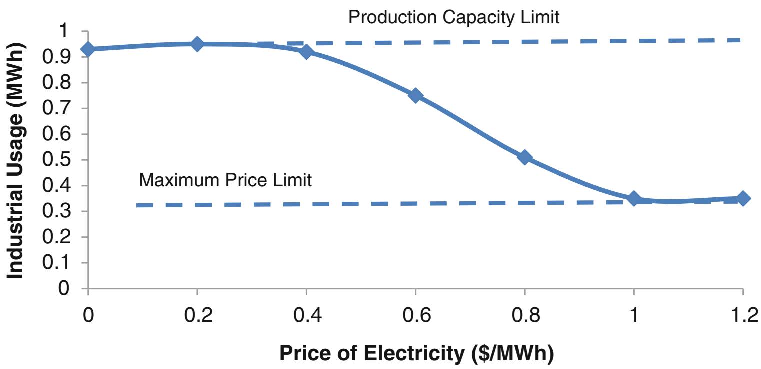


**Fig. 2.1** Nonlinear relationship between industrial usage and price of electricity

increased productivity but after some time productivity reaches a plateau. Such nonlinear relationships abound in sociotechnical systems such as energy systems. Therefore, the utility of policy-supporting analysis of an energy system but without an explicit representation and modeling of its critical nonlinear relationships is limited, at best.

### 2.1.3 Time Lags Can't Be Ignored

Delays are inherent in energy systems. Consider the case of a new investor in, say a gas-fired power plant. The major milestones of this new project, including approval of the application, securing project funding, construction, testing, and commissioning of the power plant, not only take time but often are characterized by delays. In general, these delays are of two kinds: (i) material delays [e.g., delay in the construction of power plants; e.g., on average it takes 3–4 years to build thermal power plants and 6–10 years for nuclear and hydro (reservoir-based) power plants (IAEA 1993)], and (ii) information delays (e.g., delay in the notice of approval of the application and commissioning permit, etc.). These delays have severe implications not only for the power plant investors themselves (e.g., delayed operations mean much delayed earnings leading to, say shareholders' discomfort) but also for the relevant energy planners and decision makers (e.g., the concerns of off-the-grid industry and population). Therefore, the modeling method for energy policy should have the capability to account for the potential dynamics of these inherent time lags of energy systems.

### 2.1.4 Causation Not Correlation Informs Strategic Decisions

Indeed energy policy decisions are strategic decisions: these decisions dictate the nature of the future energy supply mix and influence the associated economics for the region. It is the information about the causal nature of the relationships between the variables of the energy systems that is useful for enacting an integrated energy policy. For instance, energy policy makers are interested in knowing the influence (s) of the various stocks of the energy system, such as how the stock of "electricity capital" (i.e., various power plants) impacts electricity prices over time. Or which electricity supply mix can provide affordable and cleaner electricity? What would be the long-term impact of certain policy regulations and incentives? Therefore, the candidate modeling method for energy policy should not only be able to represent such causal relationships in the model but also provide information on the dynamics of these influences.

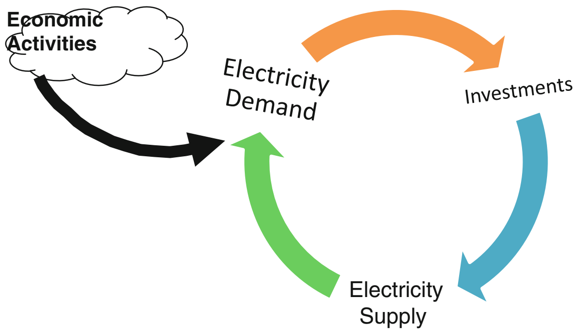


**Fig. 2.2** A demand–supply balancing feedback loop

### *2.1.5 Energy Systems Are Essentially Feedback Systems*

Increased economic activities lead to higher electricity demand. Higher electricity demand requires new investments. New investments, after some delays, provide more electricity to close the loop (i.e., either the demand is fulfilled or the cycle, demand → investments → supply → demand, continues until the demand is fully met). Such a cycle is essentially a feedback loop where three variables of an energy system, demand, investments, and supply, are responsible for the resulting dynamic behavior of this feedback loop (as is shown in Fig. 2.2).

There exist several such feedback loops in an energy system and they are interact with each other to produce the dynamic behavior of the energy system (e.g., a particular trajectory of electricity prices, environmental emissions, the stock of renewable technologies (e.g., windmills), sector-related employment, etc.), much needed information for the decision makers to enact a systematic and integrated energy policy. Traditional modeling approaches are hardly adequate for providing such a feedback-oriented analysis of the energy systems to the energy policy decision makers.

## 2.2 Summary

Overall, modeling and simulation have well served the energy domain for well several decades.

The existence of nonlinear and uncertainty intensive variables, several inherent time lags, and intertwined feedback loops in an energy system pose serious modeling challenges. Now, the increasing liberalization and privatization, heightened emphasis on environmental issues including global warming and climate change, complexity of multidimensional and conflicting interests of stakeholders, and unprecedented technological disruptions have only added to the complexity of the task for energy policy decision makers across the globe. In the context of these forceful developments, the traditional econometric methods and linear programming methods alone are not adequate to deal with the complex dynamic nature of energy policy issues. How do we deal with such complex systems? System dynamics methodology (Forrester 1961) rises to this challenge. Chapter 3, provides details on this promising assertion.

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