Applied Energy 228 (2018) 1640–1655

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Reduced-form models for power market risk analysis☆

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HIGHLIGHTS

- The complexity of electric market models limits their usefulness in risk analysis.
- A reduced-form modeling approach is developed using neural networks.
- The reduced-form model enables the use of modern, simulation-based risk analysis.
- Applications to the analysis of the cash flow risks of generators are explored.

ARTICLE INFO

Keywords:
Electric power generation
Monte Carlo simulation
Neural networks
Quantitative risk analysis
Reduced-form modeling

ABSTRACT

The experience of the last fifteen years has illustrated dramatically the emergence of new risks facing power market investors. The volatility of commodity prices, the strategic behavior of competing firms, and regulatory uncertainty all contribute to a challenging investment and operating environment. Traditionally, utilities and power-market investors have used large-scale optimizing production-cost models to analyze the cash flows of power generators. The complexity of these models, particularly when applied on a regional or national scale, is such that computational costs often prohibit extensive analysis of commodity, regulatory, and structural risks. This article demonstrates how a reduced-form modeling approach utilizing neural networks can be used to increase greatly the ability of modelers to use modern simulation-based risk analysis techniques. In particular, several applications relevant to evaluating the cash flow risks of generators, with applications to hedging, are presented. Central to the contributions of this paper is our reduction of complex optimizing models to spreadsheet form, reducing not only their computational complexity, but also their practical user complexity.

1. Introduction

1.1. A need for new tools for a changing world

Since deregulation, investors in the U.S. electric power generation sector have seen a significant increase in the types and amounts of risk, and therefore in the need for new risk analysis tools [1]. As the industry shifted from a world dominated by cost-of-service regulation and central planning to one featuring competition and profit-maximization in many regions, new risks have emerged to confront investors. In the past, under traditional cost-of-service regulation, power generators had more flexibility to deal with suboptimal decision making. Today, however, with profits determined largely by competitive position or performance-based regulation, a heightened emphasis has been placed on making better, more informed decisions.

Power-generation owners must also cope with a shift of objectives. In the world of traditional regulation, the objective was to minimize aggregate system costs while maintaining reliability; in a competitive world, the objective is to maximize firm profits, subject to a reliability, environmental, and market power constraints. As Nanduri and Das [1] did a decade ago, Li and Trutnevyte [2] stress the need for new tools to assist with long-term investment planning. For many generators, the certainty of fixed, long-term contracts for power and fuel has disappeared. Generator owners that were previously concerned primarily with operational issues, given their fixed operating margins, must now cope with a world in which their operating margins are at the whim of extremely volatile commodity prices (such as electricity and natural gas), the strategic behavior of their competitors, and regulatory uncertainty.

To power generators, risk management traditionally meant

☆ This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
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https://doi.org/10.1016/j.apenergy.2018.07.044
Received 30 October 2017; Received in revised form 28 June 2018; Accepted 12 July 2018
0306-2619/

managing the rate-setting process and, from an operational perspective, minimizing risks to reliability. The idea that power generators and utilities would need to address commodity price, strategic, and regulatory risks was less emphasized. As a result, utilities typically relied on production-cost models (PCM) to guide their dispatch and long-term planning decisions [3]. These optimization models, such as AURORA, GE-MAPS, PROMOD, and others, are computational models designed to calculate a system's production costs, availability, fuel consumption, and various other factors related to generator operation. They usually involve modeling not only generation characteristics, but also fuel supply, economic dispatch, unit commitment, and hydrothermal coordination [4].

Although modeling power-system equilibrium is relatively straightforward in theory, in practice these problems often possess considerable complexity. This complexity arises not only from the computational complexity of tasks such as the security-constrained unit commitment and network-flow problems [5], but also from the need to reflect strategic behavior [6–9], regulatory uncertainty [10–12], and the sheer scale of attempting to replicate entire regions on a unit-by-unit and day-by-day or hour-by-hour basis.

Even with fast computers or parallelization, these models can often take minutes to hours to solve (depending on the problem scale). Denton et al. [13] note that long-term asset valuation requires extending PCMs well into the future, but that their inability to address uncertainty is a drawback because a multiyear simulation requires "compute times on the order of an hour" for a single, well-defined future world. Indeed, energy system modeling more broadly often faces computational constraints. A similar supply chain optimization model for biomass reported computing requirements exceeding five hours [14]. Dealing with this complexity involves making tradeoffs. De Jonghe et al. [15] incorporated operational simplifications and limited their model's horizon to one year. Welsch et al. [16], in contrast, incorporated long-term planning, but with limited time slices in the form of monthly resolution. Koltsaklis and Georgiadis [17] and Wierzbowski et al. [18] incorporated both short- *and* long-term planning but included no uncertainty. As a result, risk analysis modeling has typically been limited primarily to short-term horizons (six to twelve months) for computational reasons [19,20], though exceptions exist in some cases [21]. In addition to the stochastic challenges of long-term system planning, such long-term horizons typically also require some degree of "interactivity," in that the actions of future decision-makers must be modeled [22].

If generators still existed in the relatively certain, regulated world of the past, computational effort would be of little consequence. Decision making often took place on a scale of months and years—mostly for long-term capacity planning. A handful of "sensitivity" model runs were often sufficient to represent the expected consequences of future actions. As uncertainty entered the picture, however, these models have become increasingly deficient; in many respects, they are tools designed for a different era.

One hallmark of quantitative risk analysis is the ability to reflect the probabilistic nature of risk in models as a measure of the uncertainty faced. For example, rather than assuming that natural gas prices will be $3/MMbtu in a given period, one may instead wish to model natural gas prices as emerging from some stochastic process, correlated to power prices and regional capacity planning decisions. Again, in principle, this would appear straightforward: simply run the PCMs for thousands of iterations, reflecting the multiplicity of possible future states of the world. In practice, of course, this is generally not feasible [20]. Applications of stochastic analysis in such models often face limits on both the quantity and nature of the inputs and outputs and the types of risk analysis capable of being performed [23,24].

1.2. Using reduced-form models to manage model complexity

PCMs are sufficiently complex that true Monte Carlo simulation analysis is generally impractical on any meaningful or descriptively-rich scale. Any single calculation that takes any time at all to compute renders simulation analysis paralyzed under the number of iterations required. Ventosa et al. [25] describe a three-part classification of electric market models into *optimization* (i.e., solving the production problem for individual generators), *equilibrium* (i.e., determining equilibrium across all market participants), or *simulation* (i.e., evaluating the risks to market participants from input uncertainties) because of the computational difficulties of incorporating all three elements into a single model. However, a manager's ability to use such models as decision-making tools is significantly compromised if "desktop" flexibility and comprehensiveness are impaired. If managers must wait days for the results of a single simulation analysis or are forced to juggle multiple models for different analytical purposes, the models cease to be useful in practice.

The goal of the research described in this paper is to design an approximation (a "reduced-form model" (RFM) or "surrogate" model) of a PCM that is accurate, fast, flexible, and only produces the information needed by the decision makers. To maintain its usefulness as a management decision-making tool, it is also highly desirable to maintain the entire model inside of a spreadsheet package that addresses all three of the applications in Ventosa et al. [25].

Electric power generation is not the only field in which reduced-form models are used. Mendelsohn et al. [26] used RFMs to incorporate climate impacts in economic equilibrium models. Lutz et al. [27] used RFMs to model population dynamics, noting the difficulty of assessing the right level of detail to incorporate in construction of the RFM. Zheng et al. [28] used RFMs to introduce confidence intervals to electricity price forecasts. Areas such as environmental planning [29] and even credit risk modeling [30,31] have all made extensive use of reduced-form modeling techniques—in most cases to facilitate the use of simulation analysis. The use of a RFM to facilitate simulation analysis of a large supply chain model illustrated their usefulness in tackling high dimensional problems [32]. Recent examples of their use include An et al. [33], who developed an RFM for groundwater management. Their application was notable for its use of a stratified sampling technique in the model development process. Both Prada et al. [34] and Edwards et al. [35] used RFMs to "speed up" the simulation of optimizing building design models, demonstrating considerable success within that application.

Our paper makes several novel contributions. First, we build on the integration of variance reduction techniques in [33] by incorporating a scenario generation simulation prior to estimation of the RFM. The purpose of this "pre-simulation" step is to enhance the training process by focusing not just on efficiently-selected inputs, but also on the incorporation of future decision-making agents in the construction of *plausible* scenarios. Second, our extraction of the RFM into a spreadsheet facilitates detailed simulation analysis at the desktop-computing level. Third, the reduction of the PCM into a spreadsheet model allows management-level interconnectivity with traditional investment analysis spreadsheet tools, such as discounted cash flow models and mean-variance portfolio analysis, as well as numerous other analytical endeavors. This end-to-end ability to evaluate investment risks by modeling both macro- (system) *and* micro- (generator) level uncertainty in a directly coordinated fashion within a spreadsheet framework is, we believe, unique in the electric power literature. We believe there is considerable value in removing as much distance as possible between modeling and management.

The next section provides an overview of the four steps of the modeling process developed. Section 3 outlines the component of the modeling process used to bound the range of future worlds that the model can explore and discusses the issues involved in a practical example that is continued throughout the remainder of this paper. Section 4 discusses the role of traditional PCMs in the modeling process and their outputs. Section 5 outlines the role of neural networks in the reduced-form modeling process. Section 6 describes the policy simulation