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Forecasting spikes in electricity prices

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ABSTRACT

In many electricity markets, retailers purchase electricity at an unregulated spot price and sell to consumers at a heavily regulated price. Consequently, the occurrence of spikes in the spot electricity price represents a major source of risk for retailers, and the forecasting of these price spikes is important for effective risk management. Traditional approaches to modelling electricity prices have aimed to predict the trajectory of spot prices. In contrast, this paper focuses on the prediction of price spikes. The time series of price spikes is treated as a discrete-time point process, and a nonlinear variant of the autoregressive conditional hazard model is used to model this process. The model is estimated using half-hourly data from the Australian electricity market for the period 1 March 2001 to 30 June 2007. One-step-ahead forecasts of the probability of a price spike are then generated for each half hour in the forecast period, 1 July 2007 to 30 September 2007. The forecasting performance of the model is then evaluated against a benchmark that is consistent with the assumptions of commonly-used electricity pricing models.

1. Introduction

In the mid 1990s, the regional electricity markets of New South Wales, Queensland, Victoria, South Australia, and the Australian Capital Territory were merged to form the National Electricity Market (NEM) in Australia.[1] The NEM operates as a pooled market in which all of the available supply to a region is aggregated and generators are dispatched in order to satisfy the demand as cost effectively as possible. If, in any given region, the local demand exceeds the local supply or the electricity in a neighbouring region is sufficiently inexpensive to warrant transmission, then electricity is imported and exported between regions, subject to the physical constraints of the transmission infrastructure. In terms of the composition of the supply side, coal-fired generators and hydroelectric production have a low marginal cost of production, and supply 84% and 7.2% of the NEM's capacity, respectively. Gas turbines and oil-fired plants supply around 8.5% and 0.3% of the market, respectively, and only take around 20 min to initiate generation, but have a comparatively high marginal cost of production, typically operating only during peak periods.

Wholesale trading in electricity is conducted as a spot market in which the supply and demand are matched instantaneously through a centrally-coordinated dispatch process. A summary of the process for bidding, dispatch and the calculation of the spot price is as follows. Prior to 12:30 pm on the day before production, generators each bid their own supply curve, consisting of at most ten price–quantity pairs for each half-hour of the following day, subject to a floor of −$1000 and a ceiling of $10,000 per megawatt hour (MWh). Generators are free to re-bid quantities, but not prices, up to approximately five

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[1] These markets were all linked by large capacity transmission lines, with the exception of Queensland, which participated under the NEM market rules but was not physically connected to the NEM until February 2001.

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minutes before dispatch. Upon the receipt of bids from all generators, the supply curves are aggregated, and generators are dispatched in line with their bids so that the demand is satisfied as inexpensively as possible.[2] The dispatch price for each five-minute interval is the bid price of the marginal generator dispatched into production. The spot price for each half-hour trading interval is then calculated as the arithmetic mean of the six five-minute interval dispatch prices observed within the half-hour, and all transactions occurring within the half-hour are settled at the spot price.[3]

Spot electricity prices are known to exhibit sudden and very large jumps to extreme levels, a phenomenon which is usually attributed to unexpected increases in demand, unexpected shortfalls in supply, and failures of the transmission infrastructure (Geman & Roncorni, 2006). The spikes reflect the fact that the central dispatch process sometimes needs to rely on the bids of the high marginal cost of production generators in order to satisfy demand. These extreme price events, or "price spikes", are particularly hazardous for electricity retailers, who buy from the NEM at the spot price and sell to consumers at a price that is heavily regulated (Anderson, Hu, & Winchester, 2006). Consequently, improving our understanding of the factors which contribute to the occurrence of extreme price events, as well as the accurate forecasting of these events, is crucial to effective risk management in the retail energy sector. It is this forecasting problem which is the central concern of this paper.

Broadly speaking, traditional approaches to modeling electricity prices fall into three categories, namely traditional autoregressive time series models, nonlinear time series models (with a particular emphasis on Markov-switching models), and continuous-time diffusion or jump-diffusion models.[4] These models all have one common feature: they aim to characterize the trajectory of the spot price or return across time.

Taken at face value, these models appear to differ in their treatment of price spikes. Traditional autoregressive time series models treat spikes through the use of thresholds (Misiorek, Trück, & Weron, 2006), Bernoulli and Poisson jump processes (Crespo Cuaresma, Hlouskova, Kossmeier, & Obersteiner, 2004; Knittel & Roberts, 2005), and a range of heavy tailed error processes (Byström, 2005; Contreras, Espínola, Nogales, & Conejo, 2003; Garcia, Contreras, van Akkeren, & Garcia, 2005; Panagiotelis & Smith, 2008; Swider & Weber, 2007). Markov-switching models incorporate spikes by proposing different regimes, at least one of which is consistent with a state of system stress where a spike is more likely to occur (Becker, Hurn, & Pavlov, 2007; Bierbrauer, Menn, Rachev, & Trück, 2007; de Jong & Huisman, 2003; de Jong, 2006; Huisman & Mahieu, 2003; Kosater & Mosler, 2006; Weron, Bierbrauer, & Trück, 2004). Diffusion models of the spot price introduce spikes through the addition of a Poisson jump component with either a constant intensity parameter (Cartea & Figueroa, 2005; Weron et al., 2004) or a time-varying intensity parameter (Escribano, Peña, & Villaplana, 2002; Knittel & Roberts, 2005), where the intensity of the jump process is typically a linear combination of deterministic seasonal and/or diurnal factors. Within the jump diffusion approach, Chan, Gray, and van Campen (2008) separate the price volatility into jump and non-jump components, and then explore whether volatility forecasts can be improved by explicitly incorporating the jump and non-jump components of the total variation.

All of these models essentially regard price spikes as a memoryless process with an intensity that is independent of its history. However, there is evidence to suggest that the intensity of the spiking process is not homogeneous, nor is it driven by deterministic factors alone. Indeed, there appears to be a significant historical component which is important in explaining the intensity of the spiking process (Christensen, Hurn, & Lindsay, 2009). This paper complements the existing econometric literature by focusing exclusively on forecasting extreme price events, rather than on the trajectory of the price. The sequence of such events is treated as a realization of a discrete point process, and one important characteristic of the econometric model is that it embeds the information content of previous spikes. This dependence is achieved using a nonlinear variant of the autoregressive conditional hazard (ACH) model originally developed by Hamilton and Jordà (2002). Although the econometric model is developed and applied in the context of a continuous-trading market, it lends itself to adaption for dealing with extreme events in day-ahead call markets as well, since it focuses on the forecasting of extreme events and not on modeling the trajectory of electricity prices.

The empirical work is implemented using data from four regions of the NEM. The ACH framework permits the simultaneous analysis of both the historical dependence of the spike rate, and the influence of load and temperature factors. It is found that the occurrence of extreme price events displays a significant level of persistence and historical dependence, even after taking the load and temperature factors into account. In addition, spikes are found to be much more likely to occur when the load is comparatively high, as well as at times of temperature extremes, in accordance with the usual explanation for spikes outlined earlier. Importantly, the ACH model is found to provide superior half-hour-ahead forecasts of extreme price events relative to forecasts made by an unconditional model that is broadly consistent with the type of memoryless electricity-pricing model often employed in the literature. It should be noted that

[2] For example, suppose that Generator A bids 10,000 MW at −\$100/MWh and 5000 MW at \$40/MWh, and Generator B bids 5000 MW at \$20/MWh. If the prevailing demand for the five minute period is 12,000 MW, Generators A and B will be dispatched to supply 10,000 MW and 2000 MW respectively. The dispatch price will be \$20/MWh.

[3] The NEM is therefore a continuous-trading market, not to be confused with the day-ahead call markets which operate in some European markets, such as Germany, France and the Netherlands, in which prices are quoted for delivery on each hour of the following day (see, for example, Huisman, Huurman, & Mahieu, 2007).

[4] Non-traditional approaches to forecasting price movements in electricity markets include artificial neural networks and other data-mining techniques (see for example Xu & Nagasaka, 2009; Zhao, Dong, & Li, 2007). Another approach is to focus on forecasting the value-at-risk in electricity markets (Chan & Gray, 2006), rather than the actual spot price.