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Abstract. As the transition to renewable energy sources progresses, their integration makes electricity production increasingly fluctuating, also causing amplified volatility in electricity prices on energy markets. To contribute to power grid stability, utilities need to balance volatile supply through shifting demand. This measure of demand side management creates flexibility, being enabled as the integration of IS in the power grid grows. The flexibility of deferring consumption to times of lower demand or higher supply bears an economic value. We show how to quantify this value in order to support decisions on short-term consumer compensation. We adapt real options theory, which has been widely used in IS research for valuation under uncertainty. Addressing a prerequisite, we develop a stochastic process, which realistically replicates intraday electricity spot price development. We employ it in a binomial tree model to assess the value of IS-enabled flexibility in electricity demand.

Keywords: demand side management, load shifting, electricity spot price model, real options

1 Introduction

Faced with growing environmental concern and dependence on exporters of fossil commodities, several countries aim at transitioning their power supply from fossil and nuclear sources to renewable resources, such as solar and wind. The shift toward these intermittent energy sources makes electricity production increasingly fluctuating [1]. As a sole reaction, adjusting the supply curve through electricity storage would not be sufficient—neither to balance the highly volatile supply and demand, nor to offset the involved strain on the power grid. Electricity supply features peaks, e.g. prompted by non-forecasted gusts of wind, as does demand; yet, prognosis approaches remain vague. Both has stimulated the idea of intervening on the demand side as well [2].

Accommodating fluctuations of electricity production on the demand side is referred to as demand side management (DSM). Demand response (DR), another common term, is considered a subclass of DSM measures with voluntary participation, not including direct load control [2]. For our approach, we use the term DSM, which we define as the entirety of activities influencing the timing and magnitude of consumer demand for

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electricity. Advanced Metering Infrastructure (AMI)—the totality of systems for measuring, collecting, and analyzing energy usage data—is an IT enabler for DSM. AMI combines smart meters, which measure electricity consumption in time intervals, and bidirectional communication streams between utilities and consumers [3], [4]. Utilities can thereby remotely control demand, particularly emit control signals to initiate the deferral of electricity consumption to times of higher supply or lower demand, so-called load shifting (LS). By allowing utilities to influence when certain appliances draw on electricity, consumers are providing flexibility. This flexibility bears economic value, because utilities can seize it to react to changing spot market prices for electricity and realize the difference to higher market prices as a profit when they shift loads to times of lower demand. Another motive is to save the dispatch of expensive back-up reserve, which is possible when LS enables influence on peaks of consumption.

Yet, the tools to shape demand provided through DSM do come at a price: utilities will need to "buy" the flexibility being granted—they need to compensate consumers for approving LS measures, and could make dynamic compensation offers in real time. Utilities will also need to invest in IS that provide the transmission medium for signals and information, support decisions on when to shift loads, initiate and control the process. Hence, to reach profitability, there is the need for an approach to quantify the economic value of individual LS measures, in consideration of electricity market information. It will help to decide on short-term compensation offers on a level of consumer supply. In our vision, every time individual loads are signaled to be deferrable, utilities will be able to determine how much shifting over the course of some hours is worth in money. They will employ algorithms enabling decisions on LS initiation and duration.

From the overarching research objective above, we derive our research question:

'What is the monetary value of IS-enabled, short-term flexibility in consumer demand for electricity when electricity price movement is uncertain?'

A model facilitating profitable LS decisions should firstly be fit for processing electricity prices as the key information. As opposed to share prices, electricity prices follow daily and seasonal patterns; this is why we use historically averaged price curves as a reference. Secondly, the model needs to be operable when price development is uncertain. Since prices are unknown prior to later delivery hours, we seek a way to derive predictions at the time of LS initiation. Some electricity markets, particularly the major European spot markets EPEX SPOT and Nord Pool Spot, offer an alternative: purchasing electricity contracts for later delivery hours in advance through intraday trade, which mitigates uncertainty. However, we strive to develop a method to value flexibility in a condition of uncertainty, which shall be generally applicable on various electricity markets, for example those in the United States.

Real-world LS comprises the course of some hours, i.e. intraday. We identify real options theory as the appropriate method to evaluate this flexibility under price uncertainty. Addressing a prerequisite, we develop a stochastic process, which realistically captures electricity spot price movement, yet is straightforward to apply. The replication of real-world spot price development, defined by a handful of parameters, opens up valuation approaches, and makes them flexible to be applied in any market situation. We further our approach by incorporating a binomial tree for analytic assessment of the deferral real option's value. This model provides foundation for an algorithm possibly to be integrated into decision support systems for short-term compensation offers.

This paper is structured as follows: in section 2, we discuss related work. In section 3, we explain our data set and conduct some necessary data evaluation. On this basis, we develop an appropriate stochastic process to describe electricity spot market prices, based on the concept of a geometric Brownian motion. We use this stochastic process to model and assess a deferral real option. Following a binomial tree approach, our real options analysis (ROA) yields a monetary value for IS-enabled flexibility in electricity consumption. We demonstrate this valuation method in a scenario of electric vehicle charging. Section 4 concludes our paper in addressing limitations and giving an outlook on further research.

2 Related Work

Preparing ground for flexibility valuation in IS-supported DSM is a contribution to energy informatics (EI). As a subfield of IS research, EI should apply "information systems thinking and skills to increase energy efficiency" [5]. We address this claim with our objective to improve the integration of electricity price information with IS for load control, in order to increase the efficiency of energy demand and realize economic potential. Watson et al. [5] suggest finding practical solutions, which we develop in a valuation model applicable to intraday decisions. Goebel et al. [6] argue that effort toward quantification of the relationship between IS-enabled DSM and realizable economic impact is needed. This type of EI research is essential to enable decisions on investment in technologies and compensations facilitating LS on a level of consumer supply.

Information and energy systems researchers have done well in addressing the issue of incongruent, highly volatile electricity supply and demand curves. Taking a design science approach, Bodenbenner et al. [7] draft a DSM system orientated toward LS application. Strüker & van Dinter [8] give a literature review on existing IS research contributions on demand response. They identify the quantification of the economic value as an open research question. Other papers have indeed prepared the ground for the valuation of flexible consumer demand: Sezgen et al. [9] address the need of quantifying "the economic value of investments in technologies that manage electricity demand in response to changing energy prices". We consider the authors' analysis of an option-valuation methodology a very important contribution; however, their model is not capable of capturing intraday flexibility. The authors leave this to follow-up work. Short-term LS realized through IS is a real-world use case. For this reason, research on valuation of intraday flexibility in energy consumption is vital.

Other scholars determine the value of flexible demand by taking simulation approaches: Biegel et al. [10] not only describe requirements for aligning flexible appliances with the electricity spot market, they also give an estimate of the cost and revenue, which depend on the magnitude of demand. Feuerriegel & Neumann [11], subsequent to [12] and [1], identify the need for quantification of DSM's economic potential. Based on statistical data, they derive an optimization problem for when to shift loads, which they evaluate in a simulation. Goebel [13] investigates a specific case of DSM application: controlled charging of a fleet of plug-in electric vehicles. By simulation, the author finds that utilities with an intelligent charging schedule are able to secure a savings potential. Similarly, Vytelingum et al. [14] introduce an adaptive algorithm for micro-storage management in smart grids. Conducting simulations, they show that their approach can generate energy cost savings for an average customer. From a reproduction of household load profiles, Gottwalt et al. [15] conclude that "an individual household can expect rather low benefits of an investment in smart appliances". The provided flexibility in electricity demand is, however, esteemed highly valuable to utilities.

Exceeding the scope of these authors' works, our objective is to develop an entire valuation approach, flexible in terms of use case and time of application, and with a higher degree of generality by incorporating a stochastic price model. Existing approaches to model electricity price development by stochastic means include the work of Schneider [16] and Benth et al. [17]. Schneider describes solutions to account for negative values in electricity spot price modelling. He fits a complex stochastic process specifically to integrate negative spot prices into pricing models for financial electricity derivatives (not real options, though). For real-world application, however, the author sees difficulties in estimating necessary parameters. Furthermore, a stochastic process with negative values cannot be transferred into common option valuation models that account for shifting the start of energy consumption to any possible period. Moore et al. [18] conduct spot market price regressions on natural gas prices. Their forecast of long-term peak price distributions is not applicable to intraday spot price development, particularly in the electricity markets. Designing a financial instrument for the purpose of hedging against price risk in the electricity spot market, Oren [19] uses a pricing model based on the assumption of a regular geometric Brownian motion process. The author concludes that the unadjusted model does not suffice to replicate electricity spot price development, leaving the formation of more realistic models to further work.

3 Valuation of IS-Enabled Flexibility in Electricity Demand

3.1 Spot Market Data Evaluation

In many power grids, electricity supply and demand are coordinated through market mechanisms [20]. Whereas utilities have secured medium- to long-term supply through generation capacity, concluded supply contracts, or acquired futures contracts, ultimately they need to bring fluctuating demand in line with supply throughout the day. Short-term balancing occurs through recourse to physical delivery markets, i.e. intraday or real-time trade, and back-up reserve provided by generators as well as select large-scale consumers [10]. On major European and American physical electricity markets, the daily price levels for short-term adjustments are initially determined through auction mechanisms on the day before delivery. The outcomes of these day-ahead markets provide the starting point for the operation of the spot markets. Spot market designs differ, however: on the large European spot markets EPEX SPOT and Nord Pool Spot, electricity contracts as traded objects can be purchased for any delivery hour of the day. By contrast, purchasing electricity in advance is not possible on the markets for the

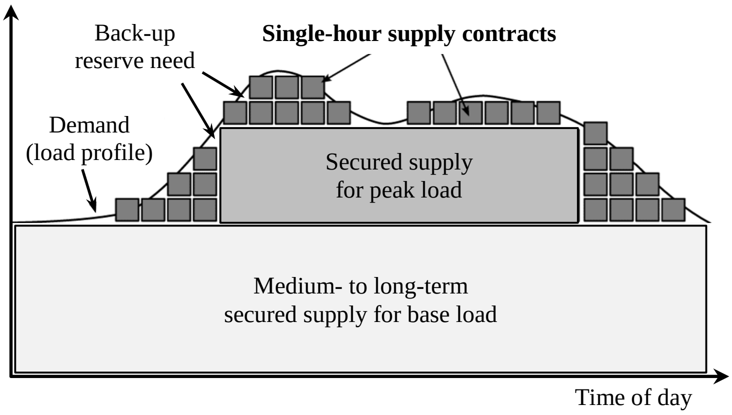

Fig. 1. Market instruments for adjusting to consumption

northeastern states of the U.S., ISO-NE and PJM, and for Texas, ERCOT, which operate real-time electricity markets. Deviation from the day-ahead schedule is possible (and settled) at the time of delivery, but not beforehand during the day.

In consequence, with respect to the situation of uncertainty in intraday price development, the American markets would be the natural application of our model. Nevertheless, it will also be faultlessly applicable on the mentioned European spot markets, where it can complement LS decisions. For reasons of data availability, we establish a model based on the European market: we study a time series of historical spot market price data from the European Power Exchange (EPEX SPOT). Trade on EPEX SPOT comprises wholesale electricity for the supply of four market areas: Germany, Austria, France, and Switzerland. Separately from French and Swiss market areas, electricity for the German and Austrian grids is traded on a shared market. For this market area, Fig. 1 illustrates the instruments available for adjusting to consumption. Balancing energy for the short term is formed by single-hour physical electricity contracts and back-up reserve. Due to their variability, the integration of renewable energy sources increases the demand for balancing energy. Dispatching back-up reserve is costly, being “compensated many times over the current spot market price and twice as high as the guaranteed feed-in tariff for renewable energy” in Germany [8]. Hence, purchase of single-hour contracts is the preferred means for adjusting to fluctuating consumption in the short term. At the same time, this indicates that on average the spot price of single-hour electricity contracts is the minimum cost of short-term supply adjustments. Thus, this type of electricity contracts is relevant for our subject of research. Whenever utilities seize flexibility to defer loads to another period by means of AMI, they realize the difference in spot market prices as a profit. In addition, this may prevent need of recourse to back-up reserve, which bears even higher economic potential.

We have retrieved our data set from Thomson Reuters Datastream. Our query has yielded final spot market prices for 24 hours on weekdays. On EPEX SPOT, traded objects are single-hour physical electricity contracts, quoted in Euro per megawatt-hour (€/MWh). Spot prices are initially the outcome of the auctions on the day-ahead market,

Table 1. Descriptive statistics for time series of spot market prices

Season	*Summer*	*Winter*	*Intermediate*	*Overall*
Spot prices				
No. of observations	4,731	4,658	9,404	18,793
No. of positive values	4,731	4,599	9,394	18,724
Mean [€/MWh]	45.51	43.98	44.43	44.95
Volatility [€/MWh]	12.32	23.58	15.39	15.55
Maximum [€/MWh]	130.27	210.00	121.97	210.00
Minimum [€/MWh]	3.02	-221.99	-49.06	-221.99
Hour-to-hour returns				
No. of returns	4,731	4,587	9,389	18,707
Mean	-0.0001	0.0031	-0.0003	0.0006
Volatility	0.1346	0.3184	0.1929	0.2193

thereafter impacted by intraday trade, up to 15 minutes before delivery time. Encompassing recent three years of spot market trade, we set the boundary dates for our analysis to 1 June 2011 and 31 May 2014. For determining the lower boundary, we have both considered the share of renewable energy sources in electricity production, and conducted a sensitivity analysis. Since 2011, more than a fifth of gross electricity consumption in Germany has been provided for through renewable energy sources. Being of this significance, their integration has impacted electricity spot prices in the market [21]. To check on sensitivity, we have conducted analogous analyses on spot price time series for recent 10, 5, 3, and 1 years: while similar daily patterns are observable, the overall price means have continuously decreased, from 48.90 to 39.11 €/MWh; this is why a shorter time series is relevant to study. Averaging three years still enables us to eliminate non-representative influences. We distinguish between summer, winter, and intermediate seasons (an ensemble of spring and autumn). Within the span of the boundary dates passed three summers (Jun–Aug; 2011–2013), three winters (Dec–Feb; 2011/12–2013/14), as well as six intermediate seasons (Mar–May, Sep–Nov; 2011–2014).

From the obtained historical data, we establish an hour-to-hour series of electricity spot market prices. Table 1 depicts descriptive statistics for these values. Negative spot prices, as seen forming the minima, are worth special consideration. On EPEX SPOT, they have been permitted in German/Austrian market areas since September 2008. They have occurred rarely so far: 69 hourly prices, an insignificant share of 0.37% of our data, valued less or equal to zero. The small flexibility of electricity production, restricted by technical and regulatory constraints, is the cause for negative prices [16]. There may be times, for example, when a surge in wind power meets little demand for electricity, or delayed reduction of power plant capacity. Due to the irregular nature of renewable energy sources, negative prices will likely occur more frequently in the future. DSM is a powerful response: firstly, such times, when monitoring IS make them known, will prove especially valuable for delivery of shifted loads. Secondly, as addressed above, IS-enabled LS can help adjust electricity consumption to fluctuating production, which will counteract excess supply. Nonetheless, the extent of the increase in non-positive electricity spot prices remains uncertain; so far, they have proven to be

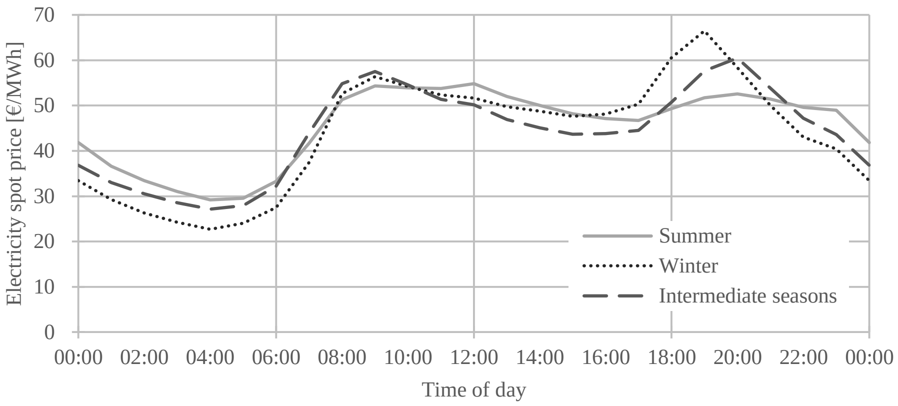

Fig. 2. Historical average daily price curves

exceptional values. Hence, we argue that working on integrating them does not need to be a priority at this point in time—it may be subject of future research. Today, faced with the uncertainty, we deem a cautionary approach appropriate: we exclude non-positive spot price values from the formation of expectations. This will not harm the result of our research, as for its application context, sensitivity would point toward a desired direction only: the value of LS would further increase with negative spot prices.

Electricity spot prices can be expected to revert toward a season-specific, long-term mean [17]. To form season- and time-specific expectations, we determine average daily price curves, as depicted in Fig. 2. These are representative for days in winter, summer, and intermediate seasons in accordance with the historical data from EPEX SPOT. Following daily life, each price curve has its minimum in the morning hours, in the spot price for electricity contracts for delivery from 4 a.m. on. A sharp increase during the morning hours is typical, until the price curves reach a plateau around 8 a.m. The price curves tend to fall in the afternoon. In the darker seasons, a substantially elevated price level is observable between 5 p.m. and 9 p.m. From 10 p.m. on, price curves for all seasons take a steady downward slope throughout the night. The stochastic process we intend to design needs to follow each of the described price movements.

We therefore transform the spot price series into geometrical hour-to-hour returns. Returns depict the change (slope) in a price curve, thus provide a measure for movement in electricity spot prices from hour to hour. Geometrical returns $\mathrm{R(t)}$ are defined as follows, with $\mathrm{S(t)}$ being the observed spot price at hour t:

$$\mathrm{R(t)} = \lg \frac{\mathrm{S(t)}}{\mathrm{S(t-1)}} \quad (1)$$

As negative and zero spot price values have been excluded from computation, the geometrical returns are computed on positive spot prices only. Table 1 also depicts descriptive statistics for these hour-to-hour returns. Volatilities provide an indication on spot price fluctuations, which require balancing by utilities and grid operators.

3.2 Adjustment of a Geometric Brownian Motion Process

We suggest assessing a utility's flexibility to shift loads by means of real options theory. Real options theory was derived from financial option valuation, which is a well-developed methodology. ROA has been applied in numerous cases in IS research [22], [23]. So far, in the energy sector, ROA has been widely applied for the evaluation of electricity generation projects [24], [25]. The capabilities of real options should also be used to assess the monetary value of IS-enabled flexibility in electricity demand with respect to uncertainty in electricity prices [9], [19]. In our model, single-hour electricity contracts serve as the underlying to a deferral option. For analytic assessment of this real option's value, a stochastic process appropriately depicting the uncertainty in the underlying's price development is a prerequisite. It should incorporate the expectation for electricity prices by assuming that spot prices tend to drift toward their long-term mean.

The square-root diffusion process [26] and the Ornstein–Uhlenbeck process [27], [28] are common mean-reverting processes for continuous-time valuation. Both require constant mean and volatility, which would hardly be adequate for our approach, since the 24 daily single-hour electricity contracts differ considerably in their long-term spot price means and volatilities. In addition, considering that physical electricity contracts are traded in hourly increments, continuous-time valuation is neither possible nor adequate. For these reasons, existing mean-reverting processes do not qualify for replicating short-term spot price movement in volatile electricity markets. Instead, from an intraday perspective, a discrete-time model suffices the simulation of electricity prices.

To achieve an appropriate stochastic process, we modify a geometric Brownian motion (GBM): a GBM is a simple stochastic process which describes deterministic and uncertain changes of an underlying value (in our case: the electricity spot price S) as a function of time t. The value change during one time step (here: the expected spot price change within one hour) is described by a term $\mu S(t)$, also called drift. With $\mu \geq 0$ being the expected relative return, the drift depicts the expected value change of the process, expressed as a fraction of its current value $S(t)$. Uncertain changes are described by a term $\sigma S(t) dW(t)$, with σ being the volatility of returns, which controls for the influence of coincidence. $W(t)$, a so-called Wiener process [29], models normally distributed returns. In summary, the GBM of $S(t)$ is described in continuous time by:

$$dS(t) = \mu S(t) dt + \sigma S(t) dW(t) \tag{2}$$

As we intend to use a discrete-time model, we can regard a single hourly increment. Consequences are, the value change in spot prices S can be set an absolute difference, and the returns of the Wiener process follow a standard normal distribution $N(0,1)$:

$$dt = 1, \quad dS(t) = S(t+1) - S(t), \quad dW(t) = N(0,1) \tag{3}$$

Altogether, in discrete time, the modeled GBM is described by:

$$S(t+1) = S(t)(1+\mu) + \sigma S(t) N(0,1) \tag{4}$$

We wish to size the process appropriately, so that it will cope with significant intraday patterns in the historical spot price data. Hence, we set the drift on every hour in a way

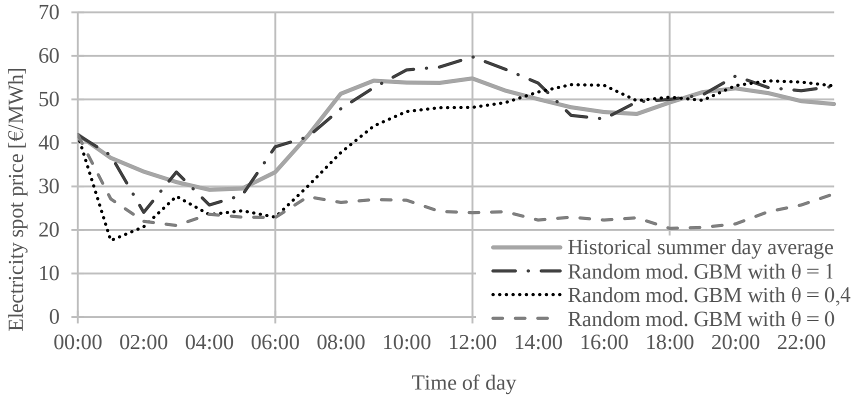

Fig. 3. Summer day simulation of modified GBM with different mean-reversion speeds

that the process reverts towards the long-term mean until the next discrete time step $t + 1$. Therefore, in continuation of the expected relative return μ introduced above, $\mu(t)$ is time-dependent and depicts the expected relative return of the process, having regard to the long-term mean of $S(t + 1)$, namely $\dot{S}(t + 1)$. As a factor for adjusting the speed of this movement, we further introduce $\theta \in [0,1]$:

$$\mu(t) = \theta \frac{\dot{S}(t+1) - S(t)}{S(t)} \tag{5}$$

Assume $\theta = 1$; this sets the expected relative return in a way that the expected value for the next hour's electricity spot price equals its historical average at that hour, which means full mean reversion. Accordingly, $\theta = 0$ means no mean reversion, whereby the process is driven by uncertainty only. Fig. 3 illustrates the influence of θ.

Uncertainty depends on a standard Wiener process, as well as on the volatility of hour-to-hour returns, which we have obtained from the historical data in accordance with definition (1). Due to large differences in historical volatility, for this parameter the time of day should be regarded, too. Thus, our model considers average, time-dependent historical returns, as well as time-dependent historical volatilities $\dot{\sigma}(t)$:

$$S(t + 1) = S(t) + \theta\left(\dot{S}(t + 1) - S(t)\right) + \dot{\sigma}(t)S(t)N(0,1) \tag{6}$$

In summary, the spot price expected for the next hour equals the currently observable spot price, tending towards the long-term mean for the next hour, and complemented by a standard normally distributed source of uncertainty. At time $t + 1$, return and volatility are adjusted, and a new GBM is created. As the result, a chain of single-period stochastic processes is tied, which constitutes a modified GBM. Fig. 3 illustrates the resulting process chain through randomly generated numbers for a summer day, in comparison to the respective historical average price curve. The diagram illustrates how simulated spot prices evolve stochastically around the long-term means. The law of large numbers indicates that a simulation averaging a sufficient quantity of randomly generated modified GBM should yield the initial average price curves. Our simulation confirms that the expected value of the modified GBM comes close to historical data. This indicates that our process provides a realistic base for a subsequent monetary valuation of LS flexibility.

3.3 Binomial Tree for Spot Price Prediction

Our objective within this subsection is to derive a binomial expression of our modified GBM (6), which enables us to assess a deferral real option's value. The traditional binomial tree model of Cox et al. [30] approximately simulates discrete-time movements of an arbitrary standard GBM [31]. It is a common approach for discrete option valuation, and suitable for ROA. Like in the traditional binomial tree model, starting point to our ROA is $t = 0$, a point in time at which a decision on initiation of LS is to be made. $S(0)$ is the spot price observable on the electricity market at this time, thus known. For any following point in time, spot prices are unknown. The tree forks at each discrete point in time t, reflecting the uncertainty in electricity spot price movement.

Under the assumption of risk-neutrality, price values can be predicted employing the modified GBM process and attributed to the nodes. In each node, spot price movement may continue in an upward or downward direction. We define $u_t \geq 1$ and $d_t \leq 1$, with $u_t d_t = 1$, as the time-dependent factors for up and down movement, respectively. Upward or downward movements are not equally likely: p_t depicts the (time-dependent) probability that the process will move into the upside scenario. In our case, this indicates the probability that the electricity spot price will increase within the next hour. $1 - p_t$ is the (time-dependent) probability for the downside scenario. In accordance with Cox et al. [30], the three parameters can be obtained as follows:

$$u_t = e^{\dot{\sigma}(t)\sqrt{\Delta t}}, \quad d_t = e^{-\dot{\sigma}(t)\sqrt{\Delta t}}, \quad p_t = \frac{e^{r_f \Delta t} - d_t}{u_t - d_t} \tag{7}$$

Δt equals 1, for single-hour time steps. Cox et al. [30] use these parameters to derive two possible future prices: $S_{u_t}(t+1) = S(t)u_t$, and $S_{d_t}(t+1) = S(t)d_t$. They allow for drifting in form of the risk-free interest rate r_f. We cannot use this variable for our mean-reverting property because the traditional model demands no arbitrage; that is, $u_t > r_f > d_t$ must be satisfied for all t. Since this is not given in our case, we modify the traditional model in two aspects: First, we set $r_f = 0$, which is appropriate since interest drilled down to one hour is insignificantly low. Second, we combine the representation of Cox et al. [30] with an additional term for mean reversion. Initially observing $S(0)$ in $t = 0$, we therefore compute the two states for the following period's spot price $S(1)$. The expressions in (8) can be mathematically proven to represent expression (6):

$$S_{u_0}(1) = S(0)u_0 + \theta\left(\dot{S}(1) - S(0)\right), \quad S_{d_0}(1) = S(0)d_0 + \theta\left(\dot{S}(1) - S(0)\right) \tag{8}$$

Fig. 4 depicts an exemplified binomial tree model with a horizon of three future periods. In a generalized form, we introduce $S_{Z_n}(t)$ for $t > 0$ as the general expression for arbitrary nodes in the tree. In an according recursion formula, Z_n indicates the composition of all states $z_n \in \{u_n, d_n\}$, which have set in over all time steps $n = \{0, \dots, t\}$ up to that

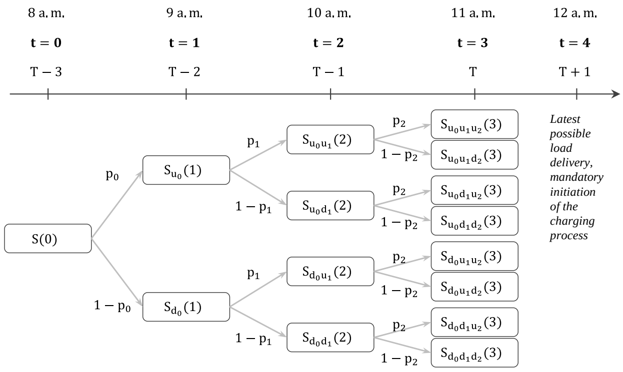

Fig. 4. Binomial tree model for an exemplified scenario

period (e.g. $Z_3 = \{z_0, z_1, z_2, z_3\}$). As explained above, we need to avoid negative prices in the binomial tree model, and therefore set the lowest possible price to zero:

$$S_{Z_n}(t) = \max\left\{S_{Z_{n-1}}(t-1) * z_{t-1} + \theta\left(\dot{S}(t) - S_{Z_{n-1}}(t-1)\right);\ 0\right\} \quad (9)$$

This modified GBM is a chain of multiple simple GBM, each calibrated in every time step. It conveys a plausible depiction of the spot price development of hourly electricity contracts, with time-dependent historical mean prices and volatilities of the hour-to-hour returns explicitly considering intraday patterns.

In order to appraise its applicability, we apply our model to a real-world scenario. Our example depicts the charging process of a plug-in electric vehicle (PEV): its commuting user reaches the workplace at 8 a.m. on a winter day, and connects it to a power outlet. The user gives the utility the right to defer the charging process throughout the morning, provided the vehicle is ready for reuse at 1 p.m. We assume that the quick charging process can be completed within one hour. Hence, electricity can be procured within one single-hour contract, but the process should be initiated no later than noon. The utility hourly decides between initiating the charging and deferring the load by another hour. In case the utility has not released the load by 11 a.m. the window for LS is closed: at noon, initiation of the charging process is mandatory.

3.4 Value determination

Although the concept of real options is distinct from financial options in the type of underlying, ROA recurs to them in one respect: a real option can be evaluated by replicating it as a financial option [32]. We can model the designed deferral option as a call option, i.e. a right, but not an obligation to buy an asset at a previously fixed price. This technical model can be interpreted in the short-term LS context: to serve a load, a utility needs to procure electricity from the market for balancing energy, single-hour electricity contracts in particular. The timing of this investment is variable; through LS, the utility gains the right to delay the purchase of the necessary electricity. Up to option maturity T, while the right to delay is valid, the utility can decide to buy (a portion of) the next available electricity contract on the spot market and emit the initiating control signal through IS. Exercising the option during that time span means expecting a monetary advantage, compared to the time of latest possible load initiation. The latter is the period after maturity $(T+1)$: if the utility has not served the load up to maturity, at that time it will be obliged to do so, because the right to defer has ceased.

We set the exercise, or strike price K equal to the long-term mean at one hour after the deferral option's maturity, so that exercising the option, i.e. serving the load, any earlier will mean an expected monetary advantage:

$$K = \dot{S}(T+1) \tag{10}$$

Therefore, a decision support system using this model would need to execute three steps iteratively in order to optimally procure electricity from the market: (a) model electricity spot price pursuant to subsection 3.3; (b) calculate option values for every node within the binomial tree by going through it systematically in reversed direction, from end nodes to root (i.e. to the point in time, at which the decision is to be made); (c) decide whether exercising the option is preferable at the current hour. If not, the system would wait for the next hour's spot price to become observable, then start again at (a). This procedure iterates until the option expires, as explained above.

As for (b), assigning option values to every node in the tree is a prerequisite for the decision between exercising the option at the current point in time and waiting until the next hour. For the end nodes (at maturity), either (i) the expected spot price is higher than strike price K, which means the mandatory delivery in $T+1$ would be preferable, so the option is worthless; or (ii), if the expected spot price is below the strike price, it would be preferable to exercise the option. Again, the composition of all states Z_T can be used to refer to individual nodes. Hence, depending on Z_T, the option values C_{Z_T} for the leafs of the tree equal the differences between the strike price and the respective current spot price, i.e. the monetary advantage, unless the option is worthless:

$$C_{Z_T}(T) = \max\{K - S_{Z_T}(T);\ 0\} \tag{11}$$

Generally, for each node within the binomial tree, we can determine the theoretical value of direct exertion (i.e. serving the load) at particular times and compositions of states. Proceeding to $T-1$ $[T-m]$, there is another possibility: since the option has not expired yet, it may be preferable not to exercise, but to wait until period T $[T-m+1]$. Since the option values for this following period have been calculated already, we can constitute an expected value, using the probability for an upside or downside scenario from (7). Having those possibilities, the option value in each node is determined as the maximum of either the value of exercising or the value of waiting. This yields the following general formula for an m-th recursion, with $m \in \{1, \dots, T\}$:

$$C_{Z_{T-m}}(T-m) = \max\left\{\begin{matrix} K - S_{Z_{T-m}}(T-m); \\ p_{T-m} * C_{Z_{T-m-1},u_{T-m}} + (1-p_{T-m}) * C_{Z_{T-m-1},d_{T-m}} \end{matrix}\right\} \tag{12}$$

After having computed all option values from T down to $t = 0$, the utility can finally decide whether exercising the option (procure electricity from the market) at the current point in time is preferable (i.e. worth more than waiting, considering the expected value of the whole binomial tree). If not, the utility would wait for the next hour's spot price to become observable, and then calculate as well as decide on an updated binomial tree again. This procedure iterates until exertion or expiration of the option. The value of LS can finally be derived by comparing the spot price at the starting point of the option (at which the load would have been served without flexibility being granted) to the purchasing price chosen by the decision support system.

Having developed this analytical approach, we have completed a method to derive the monetary value of LS. We apply the recursive valuation formulae, as developed above (with $\theta = 1$), to the PEV scenario. In order to exemplify valuation outcomes, we look at the historical spot prices for the week starting 27 January 2014. Each weekday, the PEV's user would grant LS flexibility while being at work. According to the above logic, we determine the optimal time for exercising the option and initiating the charging process inside the LS window. It would be 11 a.m. (Monday–Thursday), or noon (Friday). Over the course of the week, the realizable savings would add up to a total of 12.53 €/MWh, or 4.6%, compared to an immediate load delivery at 8 a.m. (The absolute value may be scaled to the necessary energy consumption of the PEV, which typically amounts to about 20 kWh, or a 1/50 share of a single-hour electricity contract.) From an ex-post perspective, LS savings of 20.57 €/MWh, or 7.6% would have been possible with perfect information, i.e. full knowledge of upcoming prices. In this specific example, our approach is therefore able to achieve 60.9% of possible LS savings. Further evaluations varying the time of LS initiation are subject to our future research.

4 Conclusion, Limitations, and Future Research

The transition to renewable energy sources entails demand side management efforts, with the aim to balance increasingly volatile supply through shifting demand. In this paper, we establish a method to evaluate the flexibility of deferring electricity consumption at the time it is granted by a consumer. Utilities can use the ability to quantify the monetary value of this flexibility when they decide on compensations for the consumer approving LS. Our generic model should be applicable to various electricity markets around the world. In this paper, we have studied electricity price data covering German/Austrian market areas. Whereas the according spot market would offer an alternative to procure electricity in the short term with less price uncertainty, others do not. We intend to study such, particularly North American spot markets in future work.

Further research can add to the development of incentive-compatible tariff structures, based on compensations to be offered to consumers. Moreover, scholars can design application systems for utilities integrating our valuation model in according algorithms. The value derived in our model is typically set on a lower bound, for two reasons: firstly, LS can substitute recourse to expensive back-up reserve in some cases. Secondly, in situations of excess supply, negative electricity spot prices can arise. Our stochastic process could be further developed by extending it to consider non-positive spot prices. Additionally, we have not accounted for short-term effects on electricity prices, such as weather and special events (e.g. soccer world cup finals). To capture meteorological influence, the model might relate to deviation from the temperature, wind speed, and sunshine hours medians over the entire electricity market area (market prices cannot reflect local forecasts). Further research could consequently add an adjustment factor "ρ" which should be calculated specifically to day or even hour, then multiplied by the long-term mean for the next hour $\dot{S}(t + 1)$ as well as the strike price K. If a day's electricity prices are, for example, expected to exceed the long-term mean, the model can account for such short-term effects by setting $\rho > 1$. ρ could be calculated employing a factor model quantifying and weighing all relevant short-term effects. After introducing our model, we just exemplified valuation outcomes. To conduct an evaluation, we plan to undertake simulations with random parameters.

As we use a formal modelling approach, two further, rather technical, limitations are to be mentioned: firstly, we use a standard Wiener process to describe uncertainty, which implies normal distributions. Yet, electricity prices feature rather heavy-tailed distributions [33]. Secondly, determining the factor for mean-reversion speed bringing the stochastic process the closest to the real world might capture price development more accurately. Hence, our modified GBM is just a simplification of reality, but it proves useful by enabling ROA. Such valuation methods can help assess the economic potential of IS-enabled, short-term flexibility in consumer demand for electricity.

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