An Electricity Market Model to Estimate the Marginal Value of Wind in an Adapting System

Derk J. Swider
Institute of Energy Economics and the Rational Use of Energy
University of Stuttgart, Germany
Email: djswider@ier.uni-stuttgart.de

Christoph Weber
Chair for Energy Management
University of Duisburg-Essen, Germany
Email: christoph_weber@uni-duisburg-essen.de

Abstract— **In this paper a stochastic fundamental electricity market model is presented. The model's principle is cost minimization by determining the marginal system costs mainly as a function of available generation and transmission capacities, primary energy prices, plant characteristics and electricity demand. To obtain appropriate estimates of the marginal value of wind in an adapting system notably reduced efficiencies at part load, start-up costs and reserve power requirements are taken into account. The intermittency of wind is covered by a stochastic recombining tree and the system is considered to adapt on increasing wind integration over time by endogenous modeling of investments in thermal power plants. Exemplary results are presented for a German case study.**

I. Introduction

Within the European Union large amounts of intermittent wind generation are expected to be integrated in the electricity system in the coming years. Due to the fluctuating nature this will influence the performance of the whole system and will hence add costs to the overall system operation. This leads to a strong scientific and public interest in models for estimating the costs of wind integration in electricity systems.

Debates on large-scale wind integration mainly focus on (i) how to estimate the costs of wind's intermittency and (ii) how to apportion the costs between wind generators and system operators. These aspects are subject to current research as may be seen with some recently published reviews [1]–[3]. Within this paper a stochastic approach to determine the changing system operation costs of wind's intermittency is presented.

In the literature there is a broad diversity of methodologies to estimate the costs of wind's intermittency. Grubb assesses the operation costs of a system by analyzing the effects of a variable source on the load-duration curve [4]. This statistical analysis considers the effects on start-up costs and additional reserves in a static system. Strbac discusses the integration costs in the British electricity system [5]. The simulation approach provides a detailed breakdown of costs related to distribution, transmission, reserve and unit-commitment. Thereby the system is assumed to be static and hence does not adapt to an increased share of wind generation in the system over time. Hirst and Hild simulate a relatively small system in a given year [6]. Thereby the integration costs related to reserve and unit-commitment are estimated. DeCarolis and Keith simulate a small exemplary system and assess the costs of increased wind input in a carbon constrained world with the system assumed to be static [7]. Estimates of the costs related to transmission, reserve and unit-commitment are reported.

All of these studies are based on simulating an electricity system bottom-up. Such models can be expected to be a good choice in order to estimate changing system operation costs due to large-scale wind integration, however, they neglect the uncertainties in predicting intermittent sources. Hence, so far research focused on static simulation models or deterministic electricity market models. Thus the question remains: What is the optimal system operation considering all relevant states of the stochastic wind generation? A solution to this problem can be found with a stochastic electricity market model.

In this paper such a model based on a stochastic recombining tree and an optimization of the cost minimal system operation is presented. Thereby the system is allowed to adapt on increasing wind integration and energy policies, i. e. increasing CO_2 prices, by taking endogenous investments in conventional thermal power plants into account. In a case study the model is applied to estimate the changing system operation costs due to large-scale wind integration in Germany.

The paper is organized as follows: The stochastic fundamental electricity market model is discussed in Section II. The parameters of a Germany case study are presented in Section III. The effects of stochastic electricity market modeling on changing system operation costs due to large-scale wind integration are analyzed in Section IV. Finally, conclusions and indications for further research are drawn in Section V.

II. Model description

The basic idea of fundamental models is to analyze power markets based on a description of generation, transmission and demand, combining the technical and economical aspects. These models often aim at explaining electricity prices from the marginal generation costs. Of course, this basic approach has to be extended into several directions in order to cope with the reality in electricity markets. In this paper the innovative element is that the intermittency of wind is represented by a stochastic recombining tree. In the following first the general approach is discussed. Based on this discussion a deterministic version of the model is described. This is followed by a discussion of the stochastic extension of the model. Figure 1 gives an overview of the symbols used.

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Variables			
E	Transmission flow	OC	Operating costs
FC	Fix costs	Q	Production
H	Storage level	S	Stochastic stages
L	Capacity	SC	Start-up costs
N	Nodes	TC	Total costs
Indices			
0	Minimal	r	Region
cyc	Cycling	res	Power reserve
irr	Irreversible	rev	Reversible
m	Marginal	s	Stochastic Stage
n	Node	stu	Start-up
new	New	t	Time step
old	Old	T	Final time step
onl	Online	u	Unit type
pum	Pumping		
Parameters			
a	Annuity factor	lt	Lifetime
d	Duration	oc	Other variable costs
D	Energy demand	sc	Specific start-up costs
f	Frequency	W	Water interflow
fc	Specific fix costs	η	Efficiency
fp	Fuel price	ψ	Occurring probability
i	Interest rate	ρ	Availability
lf	Load factor	τ	Transition probability

Fig. 1. Symbols used in the model

A. General approach

For the practical implementation of any fundamental model, especially if the costs of wind integration are to be estimated, at least the following six challenges arise:

- existing capacities,
- unit-commitment,
- investments,
- time resolution,
- regional resolution and
- stochastic modeling.

All fundamental electricity market models depend on the representation of the power plant portfolio of the considered system. The number and types of power plants represented may vary according to the considered regions and time horizon. With respect to the restricted computing time it may then be necessary not to model all plants separately. One attractive solution is to group the plants to classes according to the main fuel and vintage. Besides often focused thermal power plants, cf. e. g. [7], hydro power plants play a considerable role in many electric power systems. Notably, hydro storage plants require a modeling approach that encompasses several time steps and possibly stochastic inflows.

In order to cope with the intermittency of wind the operation of other units in the power system may change. Thereby the value of flexibility of plant operation to maintain a constant reliability margin may increase. Thus important aspects to be considered are start-up costs and part-load efficiencies. Those are typically modeled using binary variables, cf. [8]. But this is hardly feasible modeling of a supra-regional market.

With the integration of wind in an existing system the remaining will co-evolve over time. All else equal, the costs of intermittency will be less if the generation mix is dominated by flexible plants, i. e. by gas turbines. Hence, the consideration of intermittent wind may lead to a change in the macroeconomic cost-minimized investment behavior that need to be taken into account. Thus the estimation of changing system operation costs need to be based on a dynamic representation of the system. This may be based on a mixed-integer representation of investment decisions, cf. e. g. [9], but again this is hardly feasible modeling a supra-regional market.

As this paper focusses on changing system operation costs due to intermittent wind generation, the time resolution should be as detailed as possible. In general the modeling of seasonal hydro storage necessitates to consider a full year and the effects of intermittency on the unit-commitment of the overall system requires to consider an almost hourly time resolution. On the other hand the evolvement of wind has to be considered over a reasonable time horizon. Hence, each year of the time horizon needs to be modeled subsequently and the restricted computing time leads to use load segments within a seasonally decomposed yearly model or to model typical days that comprise a defined set of typical time segments.

With regard to the integration of a possible high amount of wind power in future electricity system configurations, the consideration of transmission constraints is of high importance. A fundamental model may therefore be divided in different geographic entities. They should preferably represent today's transmission system in a way that possible transmission constraints can sufficiently be modeled. Some authors argue that, on balance, future electricity imports and exports will be more or less the same [9]. Hence, a regional model without considering the transmission net may be sufficient to represent the future power system.

This however neglects (i) the different evolvement of power systems over time and (ii) the spatial distribution of wind. The different evolvement is mainly due to local energy policies. Consider, for example, the nuclear policy in Germany and France. In Germany a phase-out has been decided on whereas in France investments in nuclear power plants are still possible. Hence, the relative supply curves of the systems may change. This may lead to higher imports of comparably inexpensive electricity produced by nuclear power plants in France to Germany. Hence, if connected electricity systems are modeled over a longer time horizon the future electricity transmission may not stay constant.

The spatial distribution is another aspect that may lead to model the transmission net in greater detail. The German power system, for example, is defined by a high concentration of installed wind power in the coastal regions in the north. By contrast the electricity demand in these regions is rather low compared to the consumption in the south.

In general stochastic fluctuations are particularly relevant if the model is to be directly used for short-term predictions or to give an estimate of the effects and additional costs of wind's intermittency. As highlighted above most models to asses integration costs of wind are based on a simulation rather than an optimization. Thereby the fluctuations are considered with a defined process of wind generation over time. This accounts well for actual variations in the wind generation but does not account for the additional uncertainty conventional generators have to face. The uncertainty is due to the wind generation being more or less unknown for the next hours and leads to a changing optimal operation of the system. To cope with this uncertainty two principal stochastic approaches are possible to be used in a fundamental electricity market model: (i) a branching tree and (ii) a recombining tree. While the former is well suited for a shorter time horizon, the latter has advantages if a longer time horizon is considered.

B. Deterministic model

The model determines the marginal generation costs as a function of available generation and transmission capacities, primary energy prices, plant characteristics and actual electricity demand. Additionally the impact of hydro-storage and start-up costs as well as endogenous investment decisions are accounted for. The principle of the model is cost minimization in the considered power network. The deterministic objective function to be minimized can thus be written as:

$$TC = \sum_r \sum_u \sum_t d_t\, f_t\, (OC_{r,u,t} + SC_{r,u,t} + FC_{r,u,t}) \quad (1)$$

Thereby the total costs TC are minimized and are calculated by the sum of operating costs $OC_{r,u,t}$, corresponding start-up costs $SC_{r,u,t}$ and fix costs $FC_{r,u,t}$ subject to region r, unit type u and time segment t. This sum is weighted by the duration d_t and frequency f_t of a time segment.

The operating costs $OC_{r,u,t}$ are assumed to be an affine function of the decision variable of the plant output $Q_{r,u,t}$. Thereby the decision variable of capacity currently online $L^{\mathrm{onl}}_{r,u,t}$ is introduced [10]. The capacity online generally forms an upper bound and, multiplied with the minimum load factor, a lower bound to the output. This allows to describe the difference between part-load and full-load efficiency:

$$\begin{aligned} OC_{r,u,t} &= oc_u\, Q_{r,u,t} \\ &\quad + \frac{fp_{r,u,t}}{\eta^{\mathrm{m}}_u} \left(Q_{r,u,t} - l\!f_u\, L^{\mathrm{onl}}_{r,u,t}\right) + \frac{fp_{r,u,t}}{\eta^{0}_u}\, l\!f_u\, L^{\mathrm{onl}}_{r,u,t} \end{aligned} \quad (2)$$

In this equation $fp_{r,u,t}$ gives the fuel price, η^{m}_u the efficiency at full load and η^0_u the efficiency at the minimum load factor $l\!f_u$. The efficiencies are assumed to be constant and as $\eta^{\mathrm{m}}_u > \eta^0_u$ the operators have an incentive to reduce the capacity online. Furthermore other variable costs oc_u are included.

Start-up costs may influence the unit-commitment decisions considerably. In order to avoid binary variables again the capacity currently online $L^{\mathrm{onl}}_{r,u,t}$ is used. With this the specific start-up costs sc_u arise, if the capacity online is increased, i. e. if the start-up capacity $L^{\mathrm{stu}}_{r,u,t} = L^{\mathrm{onl}}_{r,u,t} - L^{\mathrm{onl}}_{r,u,t-1}$ gets positive. The total start-up costs $SC_{u,t}$ are then described by:

$$SC_{r,u,t} = sc_u\, L^{\mathrm{stu}}_{r,u,t} \quad (3)$$

Contrarily to many other fundamental market models endogenous investments in new conventional thermal power plants are taken into account. This reflects that the system may change due to an increased share of wind generation on total production. Hence, for calculating the fix costs $FC_{r,u,t}$ the choice among different available investment alternatives with specific irreversible fix costs fc^{irr}_u and the decision variable of newly build capacity $L^{\mathrm{new}}_{r,u,t}$ is endogenously modeled:

$$FC_{r,u,t} = a(i, lt_u)\, fc^{\mathrm{irr}}_u\, L^{\mathrm{new}}_{r,u,t} + fc^{\mathrm{rev}}_u\, L_{r,u,t} \quad (4)$$

Thereby the investments are discounted by the annuity factor $a(i, lt_u)$ defined by the interest rate i and the lifetime lt_u. Finally, also reversible specific fix costs fc^{rev}_u for the total installed power plant capacity $L_{r,u,t}$ are taken into account.

The key constraint is that supply and demand have to be identical in every region r and at every time step t:

$$\sum_u Q_{r,u,t} + \sum_{r'} (E_{r'\to r,t} - E_{r\to r',t}) \equiv D_{r,t} + \sum_u Q^{\mathrm{pum}}_{r,u,t} \quad (5)$$

Thereby the demand is exogenously given by the energy demand $D_{r,t}$ and the decision variable of export flows $E_{r\to r',t}$, while supply is given by the power production $Q_{r,u,t}$ and the decision variable of import flows $E_{r'\to r,t}$. As also pumped hydro plants are considered the decision variable of pumping energy for hydro storage $Q^{\mathrm{pum}}_{r,u,t}$ need to be added.

The production $Q_{r,u,t}$ is constrained by the total installed capacity $L_{r,u,t}$ multiplied by an availability factor $\rho_{u,t}$.

$$Q_{r,u,t} \le L_{r,u,t}\, \rho_{u,t} \quad (6)$$

The availability factor depends on the time of the year and accounts for planned outages, i. e. revisions, only. This production constraint may be formulated alike for the pumping energy $Q^{\mathrm{pum}}_{r,u,t}$ and, as a transmission constraint, for the import flows $E_{r'\to r,t}$ and the export flows $E_{r\to r',t}$.

As this paper addresses the effects of large-scale integration of intermittent wind energy it is necessary to consider reserve power requirements. The reserves are estimated endogenously in the model applying a probabilistic method based on Sontow [11]. Thereby the capacity secured $L^{\mathrm{sec}}_{r,u,t}$ is calculated by estimating the probability distribution of the capacity reliable of the given power plant portfolio. This distribution can be estimated by sequentially calculating the convolutions of the probability distributions of all power plants. Given the general discrete distributions f_k and g_k being defined on the set $\mathbb{K} = \{1, 2, \ldots, K\}$ (set of capacity steps) and with $\sum_k f_k = 1$ as well as $\sum_k g_k = 1$ the convolution at index $l \in \{1, 2, \ldots, 2n-1\}$ can be calculated following:

$$z_l = f_l * g_l = \sum_{i=1}^{l} f_i\, g_{l-i+1} \quad (7)$$

For conventional plants two states are assumed: with probability p the plant is able to produce and with probability $q = 1-p$ not. In the deterministic setting this can also be assumed for the wind power plants. Hence, the only uncertainty is an unplanned outage due to technical reasons.

This convolution is repeated for all power plants. Setting the cumulative sum of the finally estimated probability of the power plant portfolio equal to a defined reliability margin directly leads to the wanted capacity secured. Then the reserve can be calculated by the difference between the capacity available and the capacity secured.

Next to these overall reserve requirements restrictions at the plant level have to be satisfied. These restrictions are included in the capacity balance equation of plants able to provide them:

$$L^{\mathrm{onl}}_{r,u,t} + L^{\mathrm{res}}_{r,u,t} \leq L_{r,u,t}\, \rho_{u,t} \tag{8}$$

When considering hydro storage plants, storage constraints need to be considered. It is thereby necessary to describe the filling and discharging. This may be obtained by constraining the decision variable of the storage level $H_{r,u,t}$, expressed in energy units, not to be greater than the level at time step $t-1$ minus the production $Q_{r,u,t}$ and plus the exogenously given inflow $W_{r,u,t}$ for all hydro storage plants.

$$H_{r,u,t} \leq H_{r,u,t-1} - Q_{r,u,t} + W_{r,u,t} \tag{9}$$

For the pumped storage plants an even further extension of the framework is required. The already introduced pumping energy $Q^{\mathrm{pum}}_{r,u,t}$ and a given cycling efficiency η^{cyc}_{u} is required.

$$H_{r,u,t} \leq H_{r,u,t-1} - Q_{r,u,t} + W_{r,u,t} + \eta^{\mathrm{cyc}}_{u}\, Q^{\mathrm{pum}}_{r,u,t} \tag{10}$$

Finally, an adequate terminal condition for the water reservoirs has to be included. One attractive formulation is to require that the final and the initial reservoir level are identical, which can be expressed through the following initial cyclical condition for the hydro plants (thereby the first time step is indicated by $t=1$ and the final time step by $t=T$):

$$H_{r,u,1} \leq H_{r,u,T} - Q_{r,u,1} + W_{r,u,1} \tag{11}$$

and for the pumped storage plants:

$$H_{r,u,1} \leq H_{r,u,T} - Q_{r,u,1} + W_{r,u,1} + \eta^{\mathrm{cyc}}_{u}\, Q^{\mathrm{pum}}_{r,u,1} \tag{12}$$

C. Stochastic model

The aforementioned equations need to be extended in order to cope with the stochastics of intermittent wind generation. Instead of considering one operation mode of the system at one moment in time, one has to consider different alternative stochastic states depending on the actual wind generation.

For representing the stochastic wind generation a recombining tree is considered. Thereby a typical day t is subdivided in S stochastic stages $s \in \{1,2,\ldots,S\}$ (that can be equal to the considered duration d_t of a time segment or may comprise several such time segments) and for each stage N stochastic states or nodes $n \in \{1,2,\ldots,N\}$ are distinguished. Following this setting, the number of decision variables increases with the power of N. Hence, the consideration of stages is due to the need to reduce the resolution of the stochastic representation in order to limit the computational burden.

The recombining tree is depicted in Figure 2. Each node is characterized by the respective value of the stochastic variable and its probability $\psi_{r,s(t),n}$ (here $s(t)$ indicates that to each time segment t a unique stochastic stage s is associated). It may be seen that each node n at stage s is coupled with each node n' at stage $s+1$. Thereby transition probabilities $\tau_{r,s\rightarrow s+1,n\rightarrow n'}$ need to be taken into account. They give the probability that a specific stochastic state is expected to follow a specific state on the proceeding stage. To be more specific: In this paper the nodes represent different stochastic states, e. g. low, medium and high wind generation, at a given stochastic stage, i. e. the wind power generation is assumed to be constant in the hours comprised by the stochastic stage. Additionally, at the end of each typical day the transition probabilities to a day of the same type and the probabilities of a shift from weekend to weekday and vice versa are taken into account.

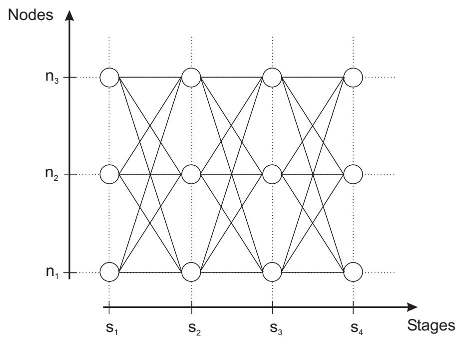


Fig. 2. Stochastic representation by a recombining tree

Following this the stochastic objective function is a straightforward extension of the deterministic approach in Eq. (1). The key point is that all decision variables are simultaneously indexed over time t and node n and that the different nodes enter the objective function with their probability $\psi_{r,s(t),n}$:

$$\begin{aligned} TC = &\sum_{r}\sum_{u}\sum_{t}\sum_{n} d_t\, f_t\, \psi_{r,s(t),n} \\ &\times\, (OC_{r,u,t,n} + SC_{r,u,t,n} + FC_{r,u,t,n}) \end{aligned} \tag{13}$$

For the other static equations it is necessary to add the index for the different nodes. The capacity, reserve and transmission constraints are examples of such static equations, cf. Eq. (6). However, for dynamic equations, which link different time steps, it is important to account for the transition probabilities. E. g. reservoir fillings at the beginning of a stochastic stage will be determined by the probability weighted average of the filling levels at all nodes of the prior stage.

In such a stochastic setting the probability distribution of wind power availability as needed to endogenously calculate the reserve power requirements can no longer assumed to be based on two-states only. Here the considered nodes and the corresponding probabilities define the probability distribution of the wind power plants. Hence, considering more nodes leads to a higher accuracy in representing the actual distribution.

III. Case Study

The description of the developed stochastic fundamental electricity market model has shown that assumptions on the regional resolution, time horizon and discount rate, generation

TABLE I

EXISTING THERMAL POWER PLANTS

Type		CF-E-40	CF-E-44	LF-E-39	LF-E-45	GT-E-28	GF-E-43	NF-E-100	MF-E-42
Fuel type	(–)	Coal	Coal	Lignite	Lignite	Gas	Gas	Nuclear	Misc
Vintage	(–)	– 79	80 –	– 79	80 –	–	–	–	–
Net capacity single plant	(MW)	150	250	400	500	50	150	1100	25
Overall capacity	(MW)	11924	13738	9084	7998	2290	16432	21181	1700
Efficiency (full load)	(%)	40	44	38	41	28	43	100	42
Availability (winter)	(%)	90	90	90	90	95	97	96	90
Reliability	(%)	95	96	96	97	92	97	99	97
Specific start-up costs	(€/kW)	32	32	19	19	49	31	4	24
Other variable costs	(€/MWh)	2.2	2.2	1.7	1.7	1.2	1.2	0.5	1.2
Fixed operation costs	(€/kW)	43	43	52	52	19	19	38	19

capacities and investments, electricity demand, energy policy and finally also on the considered stochastics are important parameters of the model. They may considerably influence the modeling results and are discussed for a German case study in the following subsections.

A. Regional resolution

The model is developed to account for several regions (within one country or between neighboring countries) coupled by defined transmission capacities. In this case study, however, such interactions are not accounted for. Thus, additional costs of transmission and distribution of wind integration are not considered. Following this discussion the analysis is based on whole Germany as the only considered region in the model.

B. Time horizon and discount rate

Here a time horizon until 2020 is considered. Thereby each year is sequentially modeled, i. e. a myopic approach is taken. The complete description of a year is omitted in order to limit the computational burden. This leads to divide each year in 12 typical days (every two months one typical weekday and weekend) and each day in 12 typical time segments.

For an appropriate choice of the discount rate, as needed to model investments, the relevant risks have to be analyzed. These risks result in the uncertainty of the economic competitiveness of the power plant investment in the longer run. Here the discount rate is assumed to be 8 %, cf. e. g. [9], [10].

C. Generation capacities and investments

All fundamental models depend on the representation of the power plant portfolio of the considered system. To reduce the complexity the power plants within this paper are grouped according to the main fuel and vintage. The characteristics of these thermal power plant classes are given in Table I. It may be noted that in the case study full- and part-load efficiencies are distinguished, cf. Eq. (2). Additionally may be noted that in the case study distinct availabilities for the two months time periods are assumed, with higher availabilities in the winter months than in the summer months. The lifetime of the considered thermal power plants is assumed to be 35 years and independent of any modernization efforts. The endogenously modeled investments are based on the data given in Table II.

TABLE II

INVESTMENT OPPORTUNITIES IN THERMAL POWER PLANTS

Type		CF-N-44	GT-N-33	GF-N-58
Fuel type	(–)	Coal	Gas	Gas
Vintage	(–)	New	New	New
Net capacity single plant	(MW)	750	150	400
Efficiency (full load)	(%)	44	33	58
Availability (winter)	(%)	92	95	97
Reliability	(%)	97	93	97
Specific start-up costs	(€/kW)	32	49	30
Other variable costs	(€/MWh)	2.2	1.2	1.2
Fixed operation costs	(€/kW)	44	11	20
Investment costs	(€/kW)	1050	230	450

Variable generation costs are mainly determined by the fuel costs. Those depend on the fuel prices and the efficiency of the respective power plant class. The development of fuel prices over time is assumed to be static, i. e. independent of investments in new power plants, and given in Table III.

TABLE III

FUEL PRICES FREE PLANT (€/MWH)

	2000	2001	2002	2003	Change (%)	2020
Coal	6.28	6.95	6.02	5.66	0.40	6.11
Lignite	3.55	3.59	3.62	3.66	0.40	3.95
Nuclear	6.14	6.14	6.14	6.14	0.00	6.14
Gas	14.54	18.68	15.87	16.65	1.10	19.97

With respect to the probabilistic approach for estimating the reserve requirements considering power plant classes leads to take care in determining the probability distribution of their availability. Note that a power plant class cannot be represented with the two-state assumption (with probability p able to produce and with probability $1-p$ not) for a single power plant. Assuming that the class represents n power plants of the same capacity and distribution for the single plant the wanted distribution for the class can be calculated by a $(n-1)$-fold convolution following:

$$z_l = f_l^{*(n-1)} = \binom{n}{l-1} p^{n-l+1} (1-p)^{l-1} \qquad (14)$$

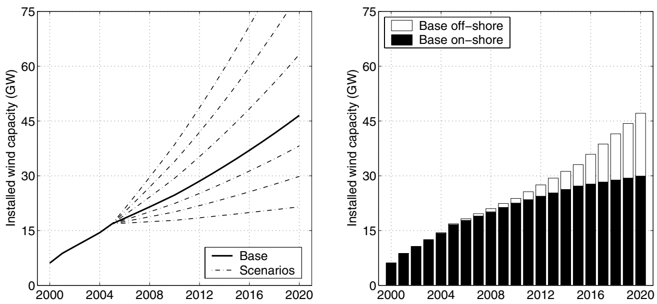
Besides the thermal power plants focused on so far, hydro-electric power plants play a considerable role in the German power system. Thereby three classes have to be distinguished: run-of-river plants, hydro storage plants and hydro storage plants with pumping facilities (pumped storage plants). In difference to the thermal power plants the costs of generation do not play such a significant role for hydro power plants. The characteristics of the considered hydro power plant classes are given in Table IV.

TABLE IV

EXISTING HYDRO ELECTRIC POWER PLANTS

Type		RR-E	HS-E	PH-E
Fuel type	(–)	Water	Water	Water
Vintage	(–)	–	–	–
Net capacity single plant	(MW)	5	5	75
Overall capacity	(MW)	2421	324	5103
Efficiency (full load)	(%)	100	100	100
Availability (winter)	(%)	99	70	70
Reliability	(%)	100	100	100
Specific start-up costs	(€/kW)	0	0	0
Other variable costs	(€/MWh)	2.5	2.5	2.5
Fixed operation costs	(€/kW)	69	25	25

Wind integration is assumed to be the result of governmental aid and is hence exogenous to the model. To analyze the effects of an increasing fraction of wind serving demand on the German power system several wind capacity deployment scenarios are considered and depicted in Figure 3.



(a) Base case and scenarios (b) Base case on- and off-shore

Fig. 3. Installed wind capacity

D. Electricity demand

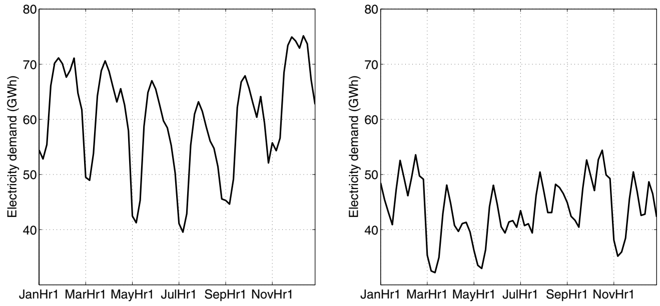
Electricity demand is assumed to be price inelastic and is exogenously given. The development over time can be handled by using predefined growth rates as given in Table V.

TABLE V

GROSS ELECTRICITY DEMAND PROVIDED BY PUBLIC PLANTS (TWH)

	2000	Change (%)	2010	Change (%)	2020
Demand	486	1.1	541	0.8	649

Electricity demand can be understood as the sum of demand of all consumer groups in Germany that result to one value for each typical time segment as given in Figure 4. It may be noted that the electricity demand is also subject to stochastic variations. However, such effects are not taken into account.



(a) Workdays (b) Weekends

Fig. 4. Electricity demand at typical time segments

E. Energy policy

To assess the effects of energy policies on the additional costs of wind integration trading of CO_2 allowances is assumed. In the European Union emissions trading started in 2005. Thereby the member states set limits on CO_2 emissions by issuing allowances as to how much companies are allowed to emit, with the reductions below the limits to be tradable. Hence, CO_2 emissions have a price. Evidently, this price is not known ex-ante, thus assumptions of the future development are necessary. In the current version of the model the price of CO_2 allowances is exogenously given by static expectations, i. e. the allowances price does not depend on a changing power plant portfolio and is given in Table VI.

TABLE VI

CO_2 ALLOWANCE PRICES (€/TCO_2)

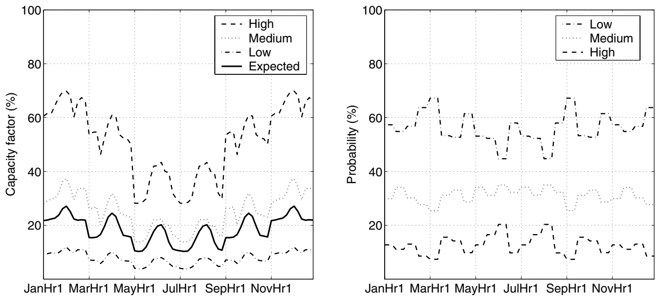
	2000 to 2004	2005	Change	2020
Price constant scenario	0	10	0	10
Price increasing scenario	0	10	2	40

The allowance costs are determined by the sum of the fuel price and the allowance price times a specific CO_2 emission factor. Those are given in tCO_2/MWh and assumed to be 0.34, 0.40 and 0.20 for coal, lignite and gas, respectively.

Besides to emissions trading the governmental decision for a nuclear phase-out in Germany is presumed (hence investments in nuclear power plants are not allowed in the model).

F. Stochastics

In the case study short-term fluctuations are of major importance. Therefore wind speed data have been combined with aggregated power curves. This is done using data from ten weather stations that reflect the spatial distribution of wind power in Germany. The time series are used to determine clusters of days with similar wind energy production. Thereby summer, winter and intermediate days are distinguished and for each six hour period cluster analyzes are carried out to identify a high, medium and low wind case as well as the corresponding probabilities of occurrence and transition. The cases (or nodes to remain in above's nomenclature of the stochastic modeling approach) give the capacity factor of wind energy production. Multiplied with the installed wind capacity this yields the actual wind generation, hence the capacity factor corresponds to the full-load hours of wind energy production. The on-shore capacity factors are given with the respective node probabilities in Figure 5.



(a) Capacity factor (b) Probability

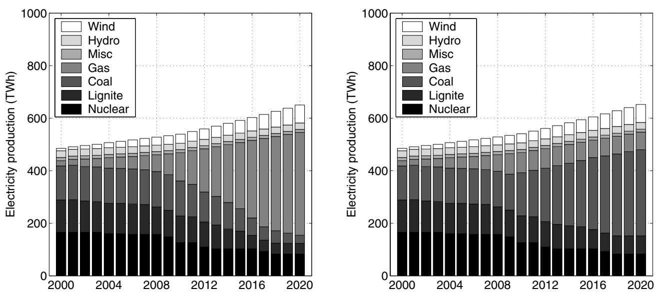
Fig. 5. Capacity factor of wind and node probability at typical time segments

Note that the capacity factor over the time horizon depends on the development of the on- and off-shore wind installations, i. e. the higher full-load hours of wind with an increased share of off-shore wind energy production are considered. Thereby full-load hours of about 1650 hrs and 2850 hrs are respectively considered for on- and off-shore wind.

Finally the constant reliability margin is set to 99 % and defines the endogenously modeled reserve power requirements.

IV. CHANGING SYSTEM COSTS

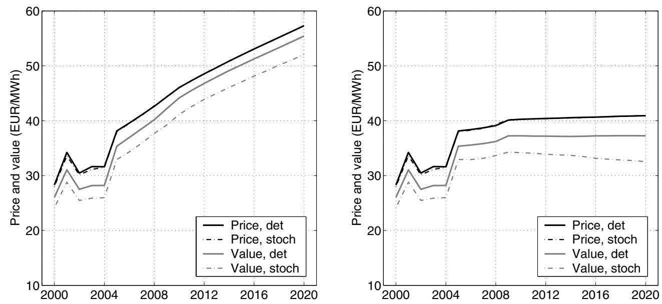
In this section results of the German case study are presented. Figure 6 gives the yearly electricity production in the base case of installed wind capacities applying the stochastic model version. It may be seen that the electricity production increases due to the increase in demand. The high allowance price case, cf. Figure 6 (a), shows high investments in gas-fired power plants, while the low allowance price case, cf. Figure 6 (b), shows high investments in coal-fired power plants. Thus the investment decisions are highly dominated by the considered allowance price paths even without considering a substantial increase of wind energy production over time.



(a) High CO_2 allowance price (b) Low CO_2 allowance price

Fig. 6. Electricity production (base case)

Figure 7 gives the development of wholesale electricity prices over a time horizon until 2020. In the model these prices correspond to the marginal generation costs and may hence be different from the spot market prices historically observed. It may be noted that the model considers Germany only and transmission, e. g. between Germany and France, is neglected. Modeling such transmission possibilities can have great impact on the prices, especially if imports of relatively inexpensive nuclear power from France to Germany is accounted for.



(a) High CO_2 allowance price (b) Low CO_2 allowance price

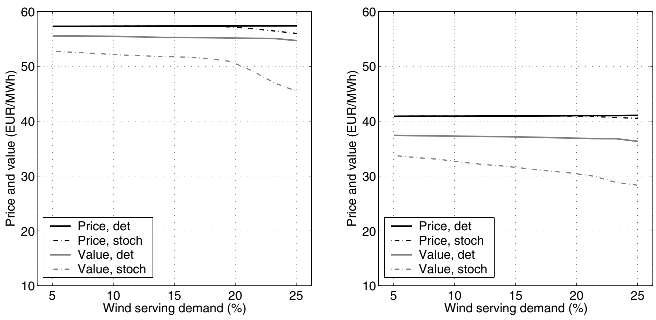
Fig. 7. Marginal electricity price and marginal value of wind (base case)

In the long-run the prices increase in case of high allowance prices, cf. Figure 7 (a), and level-out in case of low allowance prices, cf. Figure 7 (b). It may be seen that stochastic modeling of wind generation does not alter the estimated price development in the considered cases. This is due to the relatively minor impact of additional wind generation on the marginal power plant in the system. This, however, has to be taken carefully as the chosen distinction of power plant classes underestimates the sharp increase of the merit order with increasing conventional capacity. Nevertheless, it is important to note that the value of the last unit produced from wind energy may change substantially as shown in the following.

Next to the marginal electricity price Figure 7 also gives the marginal value of wind. This value is calculated as a weighted average of the hourly electricity prices, taking the wind energy production as a weighting factor. It includes avoided fuel costs, increased start-up costs and reduced part-load-efficiencies. One may see that the marginal value of wind as estimated applying the stochastic model version is generally lower than estimated applying the deterministic model version. Note that in the latter wind generation can be seen to be a firm input and may hence simply be subtracted from demand. Whereas in the former wind is assumed to be a stochastic input that hence results in a lower value of wind.

The development over time shows a relatively constant difference between the marginal electricity price and the value of wind, albeit in case of the stochastic model a slight decrease of the value can be seen. This decrease is due to the higher share of wind in the system. An additional wind turbine then reduces the marginal value of wind in the total system. This can be explained by the decreasing capacity credit with an increased share of wind in the system and increased costs for power systems reserve. It may also be seen that this effect is not accounted for in the deterministic model version. Hence, one important result of this study is that a simple deterministic model will systematically overestimate the value of wind.

Figure 8 gives the marginal electricity price and the marginal value of wind in an adapting system over a given fraction of wind serving demand. To consider the system adapting to an increased wind generation the results are given for 2020 only. This ensures that the endogenously modeled investments are taken into account. It can be seen that the increased fraction of wind serving demand has little influence on the marginal electricity price, especially if the deterministic model version is applied. However, the marginal value of wind can be seen to significantly decrease with the fraction of wind serving demand, with lower values if stochastic modeling is taken into account.



(a) High CO_2 allowance price (b) Low CO_2 allowance price

Fig. 8. Marginal electricity price and marginal value of wind in an adapting system over a given fraction of wind serving demand (in 2020)

V. Conclusions

This paper provides an electricity market model to estimate the marginal value of wind in an adapting system. Thereby the stochastics of intermittent wind generation are incorporated by a recombining tree. The applicability of the proposed approach is shown with a German case study on large-scale wind integration. The results presented indicate that the value of wind is generally overestimated applying a static, deterministic model. The results highlight that next to the explicit consideration of stochastics a model applied to assess the additional costs of intermittent wind integration should be able to endogenously adapt to an increasing share of intermittent generation, i. e. endogenous investment decisions and endogenous reserve requirements need to be accounted for. The developed approach lends itself to multiple further developments, including notably the extension to further regions. But also the rules for deriving optimal investments may be developed further, contributing to getting even more realistic pictures of the market developments.

Acknowledgement

This paper presents preliminary results of ongoing research financially supported by the European Commission within the projects GreenNet (NNE5/2001/00660) and GreenNet-EU27 (EIE/04/049/S07.38561).

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