Why wind is not coal: on the economics of electricity

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Abstract – The economics of electricity is shaped by its physics. A well know example is the non-storability of electricity that cause its price to fluctuate widely. More generally, physical constraints cause electricity to be a heterogeneous good along three dimensions - time, space, and lead-time. Consequently, different generation technologies, such as coal and wind power, produce different economic goods that have a different marginal economic value. Welfare maximization or competitiveness analyses that ignore heterogeneity deliver biased estimates. This paper provides an analytical welfare-economic framework that accounts for heterogeneity for unbiased assessments of power generators. The framework offers a rigorous interpretation of commonly used cost indicators such as 'levelized electricity costs' and 'grid parity'. Heterogeneity is relevant for all generators, but especially for variable renewables such as wind and solar power. We propose a definition of 'variability', derive the opportunity costs of variability, and link that concept to the 'integration cost' literature. A literature review shows that variability can reduce the value of wind power by 20-50%. Thus it is crucial that economic analysis accounts for the physics of electricity.

Keywords – power generation, electricity sector, integrated assessment modeling, variable renewables, integration costs, welfare economics, power economics, levelized electricity cost, grid parity | *JEL – Q42, D61, C61*

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1. Introduction

Already today, in some regions the generation costs of wind power is below that of conventional power sources like coal-fired plants, and many observers expect wind costs to continue to fall. It is widely believed that this cost advantage implies wind power is competitive or economically efficient. However, this is not the case. It would be only correct if wind power was a perfect substitute of coal power, in other words, if electricity was a homogenous economic good. But electricity is heterogeneous: because electricity can hardly be stored, its value fluctuates. Therefore it matters when electricity is generated. Wind turbines and coal plants produce at different points in time, hence the marginal value of their output is different – in other words, they produce different economic goods.

Temporal heterogeneity of electricity is acknowledged in academics for a long time (Boiteux 1949, Bessembinder & Lemmon 2002, Joskow 2011). We generalize heterogeneity by pointing out that its fundamental reason is the lack of arbitrage possibilities. The physics of electricity prevent arbitrage not only over time, but along two additional dimensions: transmission is constrained, which causes electricity to be heterogeneous across space; and power plant flexibility is constrained, which causes electricity to be heterogeneous over lead-time between contract and delivery. Hence, electricity is heterogeneous in three dimensions. Electricity from wind turbines and coal-fired plants is not only economically different because it features a different temporal profile, but also because it is generated at different locations, and under different degrees of uncertainty and flexibility.

Heterogeneity has important implications for economic analysis. Welfare and competitiveness analysis that ignores heterogeneity implicitly compares marginal values and benefits of different goods. The outcome is biased results. Several applications and tools that are in practice used for policy advice and decision support implicitly ignore heterogeneity. Take the example of two commonly applied economic indicators, 'levelized costs of electricity' (LCOE) and 'grid parity'. Policy makers, analysis, and academics regularly compare different generation technologies, such as nuclear, coal, and wind power in terms of LCOE, which is the discounted live-time average generation cost (Karlynn & Schwabe 2009, Fischedick et al. 2011, IEA & NEA 2011, BSW 2011, EPIA 2011, Nitsch et al. 2011, IRENA 2012, Kost et al. 2012, EIA 2013). It is sometimes suggested or implicitly assumed that a technology is competitive or efficient once its LCOE drop below those of conventional plants. Such LCOE comparisons implicitly assume that the marginal value of these generators is identical - which is not the case. A second widely used indicator is 'grid parity', the point where generation costs drop below retail electricity prices. Some observers seem to believe that once a technology has reached grid parity, its deployment is economically efficient (Koch 2013, Fraunhofer ISE 2013). This interpretation is subject to the same misconception, as the marginals of different goods are compared.

Not only these indicators, also calibrated multi-sector models often implicitly ignore electricity's heterogeneity. Economists have for many years used calibrated macroeconomic multi-sector models for research and policy advice, starting with Leontief (1941). Today, 'integrated assessment models' (IAMs) are an important tool for assessing climate policy and the role of renewables in mitigating greenhouse gas emissions (Fischedick et al. 2011, Edenhofer et al. 2013). Such models often represent the electricity sector with one equilibrium price, implicitly assuming homogeneity.

Heterogeneity is a feature of electricity as an economic good, and not a feature of a specific generation technology. However, accounting for heterogeneity specifically relevant for variable renewables (VRE) at high penetration, since their marginal value can become quite low (Lamont 2008, Borenstein 2008, Fripp & Wiser 2008, Mills & Wiser 2012, and Hirth 2013a). Moreover, variable renewables, such as wind and solar power, have been growing rapidly during the last years, driven by technological progress, economies of scale, and deployment subsidies. Global solar PV capacity has reached 100 GW, a ten-fold increase since 2007; wind power capacity surpassed 280 GW, a three-fold increase since 2007 (REN21 2013). Several power systems now accommodate high VRE shares, including Denmark (30%), Spain (23%), Ireland (17%), and Germany (15%), according to IHS (2013). At such high shares, differences in marginal value to conventional power plants become large. The IEA (2013) forecasts that within five years, global wind capacity will double and solar PV capacity triple. Given that much of this growth is financed with tax money, the valuation of VRE is of major public relevance.

This theoretical paper provides an analytical welfare-economic framework for an assessment of power generators that explicitly accounts for heterogeneity. The framework offers a rigorous interpretation of commonly used cost indicators such as LCOE and grid parity, suggests a welfare-economic definition of 'integration costs' of VRE, and provides insights for modeling the power sector in IAMs.

Specifically, the paper contributes to the literature in the following ways. First, it offers a rigorous and general discussion of heterogeneity. We define heterogeneity formally and introduce the concept of three-dimensional heterogeneity. For each dimension, the physical constraints that cause heterogeneity are discussed. Second, we interpret electricity from different generating technologies as different goods. These goods are only imperfectly substitutable and in general have different a marginal value. Third, the paper shows how heterogeneity can be accounted for in welfare maximization and derives first-order conditions. In turns out that there are (at least) two equivalent perspectives on optimality, each corresponding to a different electricity good. This duality helps understanding why some researchers frame their analysis of wind power variability in terms of 'value' and others in terms of (integration) 'cost'. Fourth, the article offers a rigorous definition of variability and corresponding opportunity costs of variability. We argue that all generators are subject to variability - not only VRE - and that variability can only be interpreted within a framework that accounts for the heterogeneity of electricity. Specifically, if electricity was homogenous, variability of VRE and other technologies would not cause any costs. Finally, a number of methodologically remedies are proposed. We specify a new cost metric, System LCOE, that allows economically meaningful cost comparisons of different technology, discuss how electricity's heterogeneity and VRE's variability can be accounted for in integrated assessment modeling, and propose a pragmatic decomposition of variability cost that facilitates quantification.

This paper relates to five different branches of literature. First, *screening curves* have been used for decades to find the least-cost thermal capacity mix (Phillips et al. 1969, Stoughton et al. 1980, Green 2005). This paper generalizes the screening curve approach, which accounts for temporal heterogeneity only, by deriving optimality conditions for three-dimensional heterogeneity. Second, it provides theoretical foundations for the *optimal share* literature. This literature estimates the optimal generation mix from numerical power market models (Neuhoff et al. 2008, Lamont 2008, Müsgens 2013). Third, the paper expands the *marginal value* literature that estimates the marginal value of wind and solar power (Grubb 1991, Borenstein 2008, Mills & Wiser 2012). A major finding of these studies is that their marginal value decreases with the penetration rate. This study links these results to electricity's heterogeneity and shows that not only the marginal value of VRE is specific, but that all technologies have a specific marginal value – and it always decreases with penetration. Fourth, it contributes to the *integration cost* literature assesses the costs of integrating wind and solar generators into the power system (Holttinen et al. 2011, Milligan et al. 2011, NEA 2012). This study relates integration costs to heterogeneity and offers a new definition of integration cost with welfare-economic foundation such that integration cost can be interpreted as the opportunity cost of variability. Fifth, the article challenges *integrated assessment modeling*. These models incorporate wind and solar power into numerical large-scale multi-sector long-term models, for example to assess long-term climate policy (Fischedick et al. 2011, Luderer et al. 2013, Sullivan et al. 2013). We show that the low resolution of these models can bias results, and suggest remedies. This article extends and formalizes previous work (Hirth 2013a, 2014, Hirth et al. 2013, Ueckerdt et al. 2013a, 2013b).

The remainder of this paper is organized as follows. Section 2 introduces the idea of electricity as a heterogeneous good. Section 3 derives the marginal value of different power generation technologies. Section 4 argues that these value differences can be expressed in terms of 'variability cost', and proposes the metric System LCOE. Section 5 derives the first order conditions for the optimal generation mix. Section 6 proposes a decomposition of variability cost. Section 7 applies the framework developed in sections 2 to 6 to variable renewables. Section 8 concludes.

2. *Electricity is a heterogeneous good*

In many aspects, electricity is a homogenous commodity like many others. What sets electricity apart from other economic goods? More than that of other goods, the economics of electricity is shaped by its physics. Most of its economic peculiarities stem from the fact that it is not a tangible commodity that can be stored and shipped. As a consequence, electricity can be understood both as homogeneous and heterogeneous at the same time. This section sheds light on this apparent paradox and argues that electricity is not only heterogeneous over time, as academics have acknowledged for long time, bot heterogeneous along *three* dimensions.

Electricity can be seen as the archetype of a perfectly homogenous commodity: consumers cannot even distinguish electricity from different power sources, such as wind turbines or coal-fired plants.[2] In other words, electricity from different sources is perfectly substitutable, and the law of one price applies: electricity from wind is worth the same as electricity from coal. This is reflected in real-world market structure, where bilateral contracts are not fulfilled physically in the sense that electrons are delivered from one party to another, but via an 'electricity pool': generators inject energy to the grid and the consumer take out the same quantity. In liberalized markets, electricity is traded under standardized contracts on power exchanges. Hence, wholesale markets for electricity share many similarities with markets for other homogenous commodities such as crude oil, hard coal, natural gas, metals, or agricultural bulk products.

However, homogeneity applies *only at a certain point in time*. Since storing electricity is (very) costly, the price of electricity varies over time. More precisely, the power price is subject to large predictable and random fluctuations on time scales as short as days, hours, and even minutes (Bessembinder & Lemmon 2002). As a consequence, a mix of production technologies might be optimal, rather than a single technology (Bessiere 1970, Stoughton et al. 1980, Grubb 1991, Stoft 2002), and price peaks emerge (Boiteux 1949, Crew et al. 1995). Specifically, price fluctuations have implications for the valuation of wind and solar power (Lamont 2008, Borenstein 2008, Fripp & Wiser 2008, Joskow 2011, and Hirth 2013a).

Before we proceed with discussing the other two dimensions, we define 'homogeneity' and 'heterogeneity'. We call a good to be heterogeneous *if its marginal economic value varies*. More specifically, we define it to be heterogeneous along a dimension if its marginal values varies between different points p within a certain range P. For example, one dimension is time and the corresponding range is one year. We define the 'instantaneous' marginal economic value v_p' at a point p within range P as the derivative of welfare $W(q_p,\cdot)$ with respect to an increase of consumption of the good at a certain point p.

[2] In some markets, certificates of origin exist, in order to allow consumers to discriminate between different power sources (Kalkuhl et al. 2012). However, such certificates are traded independently from electricity.

$$v'_p := \frac{\partial W(q_p,\cdot)}{\partial q_p} \qquad \forall p \in P \qquad (1)$$

Hence, a good is homogeneous along a dimension if

$$v'_p \cong v'_q \qquad \forall p,q \in P \qquad (2)$$

Otherwise, the good is heterogeneous along that dimension.[3] Taking the same example, a good is heterogeneous over time if its marginal value varies significantly between two points in time during one year.

The most fundamental condition for heterogeneity is the absence of arbitrage possibilities. Heterogeneity along a dimension can only arise if arbitrage possibilities along that dimension are inhibited. For example, storable goods feature relatively little price fluctuations over time, because inventories allow for inter-temporal arbitrage.[4] In the case of electricity, non-storability prevents such arbitrage: electricity is heterogeneous in time because it can (almost) not be stored.

Now we come back to the three dimensions of electricity's heterogeneity. The physics of electricity imposes three arbitrage constraints, along the dimensions *time, space,* and *lead-time*:

- Electricity is electromagnetic energy. It can be stored directly on condensers, or indirectly as chemical energy (battery, hydrogen), kinetic energy (flywheel), or potential energy (pumped hydro storage). In all these cases, energetic transformation losses and capital costs make storage very expensive, often prohibitively expensive.[5] Hence, arbitrage over time is limited. Consequently, it is economically different to produce (or consume) electricity now or later. In other words, the storage constraint makes electricity heterogeneous over time.
- Electricity cannot be transported on ships or trucks, as tangible goods can be, but is transmitted on power lines. These lines have limited thermal capacity, and transmission is subject to losses. Moreover, Kirchhoff's circuit laws, which govern load flows in meshed networks, further constrain transmission capacity, and reactance limits transmission distances. Hence, arbitrage across space is limited. Consequently, it is economically different to produce electricity here or there. The transmission constraint makes electricity heterogeneous across space.
- In AC power systems, the demand-supply balance has to hold at every instant in time. Imbalances cause frequency deviations, which can destroy machinery and can be very costly. However, thermal power generators are limited in their ability to quickly adjust output by limits on temperature gradients on boilers and turbines (ramping and cycling constraints). Hence, arbitrage is limited across different lead-times between contract and deliver. A generator that can adjust its output on short notice tends to increase its marginal value. The flexibility constraint makes electricity heterogeneous along lead-time.

Summing up, storage 'links stuff in time', transmission 'links stuff in space', and flexibility 'links stuff in lead-time'. Since storage, transmission, and flexibility are constraint, electricity is a heterogeneous good in time, space, and lead-time. Hence, the marginal value of electricity carries three indices: $v'_{t,n,\tau}$.

'Lead-time', the third dimension, is less intuitive than the other dimensions and might merit further discussion. Think of three types of generators: stable generators that produce according

[3] This definition excludes small price variations, such as changes driven by intra-year discounting.
[4] Inventories both prohibit predictable price fluctuations and limit random price fluctuations.
[5] Hydro reservoirs allow storing kinetic energy, before it is transformed into electricity. This might be considered the only economic large-scale storage technology deployed today – but only allows shifting generation over time, not adding energy to the storage.

to a schedule that is specified one day in advance, like nuclear power; flexible generators that can quickly adjust, like gas-fired plants; and stochastic generators that are subject to day-ahead forecast errors, like wind power. If additional net demand emerges (because of higher demand or lower supply of stochastic generators), only flexible generators are able to fill the gap. The real-time price rises above the day-ahead price, hence flexible generators earn on average higher income, which reflects their higher marginal value. Contrast this with the stochastic generators: because there is oversupply whenever they generate more than expected, their average income is reduced.

Constrained arbitrage is a necessary, but not a sufficient condition for heterogeneity. Heterogeneity requires two additional conditions to be fulfilled. On the one hand, demand and/or supply conditions need to differ between points along the dimension. Take the example of time: if supply and demand would be constant over time, non-storability would not lead to price fluctuations. Only because the demand curve for electricity shifts during the course of a day, driven by diurnal pattern in human behavior, the price fluctuates. On the other hand, both demand and supply need to be less than perfectly price-elastic. For example, if the short-term supply curve (merit-order curve) was horizontal, despite demand fluctuations and non-storability, the price would remain unchanged. Taken together, these three conditions are jointly the necessary and sufficient condition for heterogeneity:

1. arbitrage constraint
2. differences in demand or supply conditions
3. non-horizontal demand and supply curves

For electricity, these three conditions are fulfilled in all three dimensions. While the time dimension has been much discussed in the literature, the other two dimensions have received much less attention. To the best of our knowledge, this is the first study to address heterogeneity along these dimensions. Table 3 summarizes the heterogeneity of electricity.

Table 1: The heterogeneity of electricity along three dimensions.

Dimension (differences between points in …)	Time	Space	Lead-time between contract and delivery
Arbitrage constraint (1st condition)	Storage (storing electricity is costly*)	Transmission (transmitting electricity is costly*)	Flexibility (ramping & cycling is costly*)
Drivers for demand / supply variations (2nd condition)	Temporal variations e.g. day-night patter, weather, plant availability	Spatial variations e.g. load centers, plants are bound to locations, weather	Uncertainty (deviation from expected conditions), e.g. due to weather

* 'Costly' both in the sense of losses (operational costs) and the opportunity costs of quantity constraints.

Many economic goods are subject to differences in demand and supply conditions (actually, consumption of almost all goods varies with day and night) and feature non-horizontal demand and supply curves. Arbitrage possibilities make those goods homogeneous. More than anything else, it is the existence of the three non-arbitrage conditions that makes electricity a peculiar economic good.

Figure 1 visualizes the three-dimensional heterogeneity of electricity. Each axis represents one dimension, time, space, and lead-time. The length of each axis represents the 'range': one year, one power system, and the complete set of spot markets. At one point in this three-dimensional space, electricity is a perfectly homogenous good. However, as physical constraints limit arbitrage between points in that space, the marginal value differs between points. This is, according to our definition, heterogeneity.

More formally, Figure 1 can be thought of as a $[TxNx\text{T}]$-Matrix where each element is the instantaneous marginal value $v'_{t,n,\tau}$ at time step $t \in T$, at node $n \in N$, and at lead-time $\tau \in \text{T}$. We call the $[TxNx\text{T}]$-Matrix $\boldsymbol{v}$ of the elements $v'_{t,n,\tau}$ the 'marginal value space'.

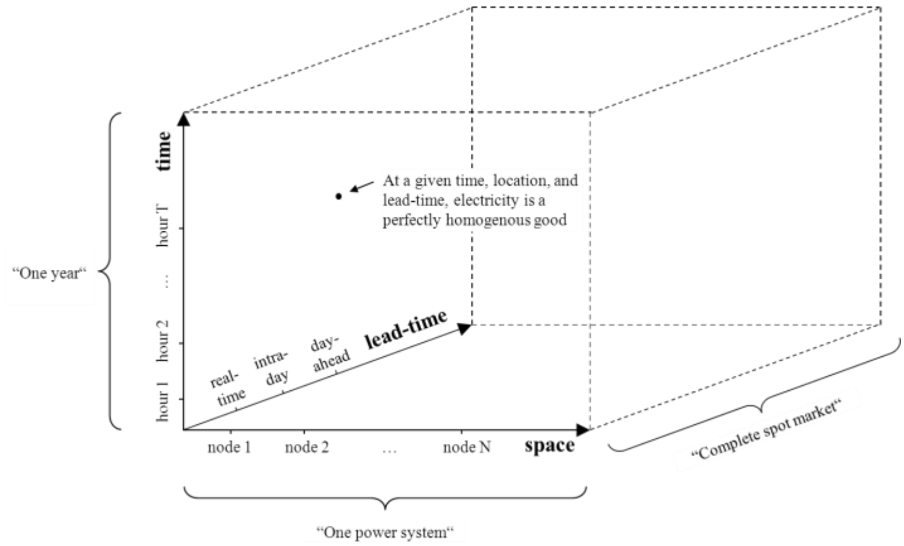

Figure 1: The marginal value space. Source: adopted from Hirth (2014).

Three-dimensional heterogeneity is reflected in reality. It can be observed in price variation, is reflected in market design, and has shaped technology development. For example, at European power exchanges, a different clearing price is determined for each hour and for each geographic bidding area. U.S. markets typically feature an even finer resolution, clearing the market every five minutes for each of several thousand transmission nodes. In addition, there is a set of power markets with different lead-times: in most European markets, there is a day-ahead market (12-36 hours before delivery), an intra-day market (few hours before delivery), and a balancing power market (close to real-time). As a consequence, there is not *one* electricity price per market and year, but 26,000 prices (in Germany) or three billion prices (in Texas).[6] Hence, Figure 1 can readily be thought off as an array of market-clearing spot prices. But not all dimensions of heterogeneity are reflected in all markets: German prices, for example, are uniform across space. Grid constraints are managed via command and control interventions.

Observed electricity prices vary along all three dimensions, as 2012 data from Germany and Texas show. The German day-ahead price varied between -222 €/MWh and 210 €/MWh, a range of ten times the average price. During a normal day, prices varied by a factor of two. Within Texas, price difference of several hundred $/MWh between different locations were not uncommon (Schumacher 2013). The spread between day-ahead and real-time price in Germany varied between -1600 €/MWh and 1400 €/MWh (Hirth & Ziegenhagen 2013). In contrast, the price of other energy carriers varies much less. The spot price for natural gas varied between 21 €/MWh and 38 €/MWh in 2012, a range of 70% of the average price; the price of crude oil between 89 $/bbl und 130 €/bbl, a range of 36% of the average price. This is in line with expectations, as storage costs for natural gas are higher than for oil, but much lower than for electricity. Within Germany, there are no significant locational spreads in gas and oil prices, which reflects low transportation cost.[7]

The heterogeneity of electricity is not only reflected in market design, but also in technology. For homogenous goods, in general one single production technology is efficient. In electricity

[6] The German spot market EPEX clears for each hour of the year as a uniform price; the ERCOT real-time market of Texas clears every five minutes for all 10,000 bus bars of the system

[7] German spot prices from EPEX Spot, Texas spot prices from ERCOT, German imbalance prices from TSO TenneT, natural gas prices from German gas hub TTF, crude oil prices for Brent.

generation, this is not the case: there exists a set of generation technologies that are efficient. ‘Base load’ plants have high investment costs and low variable costs, ‘peak load’ plants feature the opposite structure. Such peaking plants are specialized technology to supply electricity at times when it has high value, which occurs seldom. These differentiated technologies reflect temporal heterogeneity (Table 2). Some plants are quick to start up, others require much time and resources to cycle. This differentiation reflects heterogeneity in lead-time. Some plants are more compact and emit less local pollutants such that they can be constructed in load centers where the marginal value of electricity is higher; other plants are large and noisy and can only be built remotely, where their value is lower. This reflects spatial heterogeneity.

Table 2: Electricity generation technologies have adapted to temporal heterogeneity.

Technology	Annualized fixed costs (€/kWa)	Variable costs (€/MWh)	Efficient capacity factor range
Nuclear	400	10	>95%
Lignite	240	30	75% - 95%
Hard coal	170	40	50% - 75%
CCGT (natural gas)	100	55	5% - 50%
OCGT (natural gas, oil)	60	140	<5%

Cost data for central Europe with 2012 market prices for fuel, assuming a CO_2 price of 20 €/t. About 85-90% of fixed costs are capital costs. CCGTs are combined-cycle gas turbines, and OCGTs are open-cycle gas turbines. Source for technology cost parameters: Hirth (2014), based on the primary sources IEA & NEA (2011), VGB Powertech (2011), Black & Veatch (2012), and Schröder et al. (2013).

3. *The marginal economic value of an electricity generating technology*

We now characterize the marginal economic value of a power generating technology, such as nuclear, coal, or wind power. We specify the marginal value in energy terms, i.e. in €/MWh. We will argue that electricity from a different generation technology can be understood as imperfect substitutes, due to their different generation pattern in time, space, and lead-time. This section generalizes Joskow (2011) and formalizes Hirth et al. (2013).

We start with the instantaneous marginal value of electricity $v'_{t,n,\tau}$. This is given by intersection of short-term (dispatch) invers demand with the short-term marginal cost curve (merit-order curve). It is the consumers’ marginal utility and hence willingness to pay for consuming one additional unit of electricity (MWh) at time t, node n, and lead-time τ. [Under perfect and complete markets, $v'_{t,n,\tau}$ equals the locational spot price $p_{t,n,\tau}$.][8]

To evaluate a power-generating technology it is not very informative to only consider its value at one point. The mean value over a ‘range’ that is in some sense complete is more helpful for policy or investment decisions – for example the marginal value of a MWh from wind power in a country during one year, considering all spot markets. The marginal value of a generation technology is the marginal value of its output. This is the average of all $v'_{t,n,\tau}$, weighted with the generator’s output, that is the marginal value of the electricity it generates. As a range we define T to be one year, N to be one power system, and T the complete set of spot markets. Formally, the marginal value of technology i, $\bar{v}'_i$, is given by

[8] The theorems of this and the following sections hold in general; they do not depend on specific assumptions on market completeness, absence of market failures, or equilibrium assumptions. We add interpretation in terms of prices in brackets for the readers’ convenience.

$$\bar{v}_i' = \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{\tau=1}^{\mathrm{T}} g_{i,t,n,\tau} \cdot v_{t,n,\tau}' \qquad \forall i \in I \qquad (3)$$

where $g_{i,t,n,\tau}$ is the share of generation of technology i at the respective time step, node, and lead-time, such that

$$\sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{\tau=1}^{\mathrm{T}} g_{i,t,n,\tau} = 1 \qquad \forall i \in I \qquad (4)$$

We label the $[TxNx\mathrm{T}]$-Matrix $\boldsymbol{g_i}$ of the elements $g_{i,t,n,\tau}$ the 'generation pattern' of technology i. [Under perfect and complete markets, $\bar{v}_i'$ equals the market value of a technology.]

In general, the generation patterns of two technologies do not coincide.

$$g_{i,t,n,\tau} \neq g_{j,t,n,\tau} \qquad \forall i,j \in I \qquad (5)$$

Hence, in general, their marginal values do not coincide, even if considering the same year and power system.

$$\bar{v}_i' \neq \bar{v}_j' \qquad \forall i,j \in I \qquad (6)$$

They might coincide incidentally. As we will show later, in an equilibrium this is the case if the marginal costs of both generators are identical. Figure 2 illustrates that the marginal values in general do not coincide.

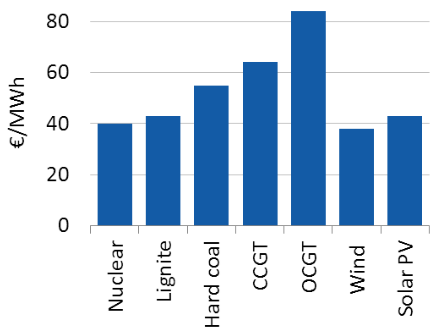

Figure 2: The marginal value of different technologies (illustrative).

To differentiate the output from different generation technologies, we define a number of economic 'electricity goods'. Each good is one MWh of electricity, but has a different pattern. We define the good I as one MWh of electricity that features the pattern $\boldsymbol{g_i}$. Hence, we define COAL and WIND[9] power as one MWh of electricity that has the same pattern as coal power plants $\boldsymbol{g_{coal}}$ and wind turbines $\boldsymbol{g_{wind}}$, respectively, hence $\bar{v}_{coal}'$ is the marginal value of the good COAL. As (6) shows, these goods have different economic values, despite representing identical energetic values. Hence, they are *only imperfectly substitutable*. While at a single point, electricity from wind and coal is perfectly substitutable, over one year (more precisely, the full range), they are not. The law of one price does not apply.

We define the marginal value of load $\bar{v}_{load}'$ as the demand-weighted average of all $v_{t,n,\tau}'$.

[9] We denote these 'electricity goods' with SMALL CAPS to distinguish them from the technology itself. Hence, 'wind' refers to wind turbines while 'WIND' refers to one MWh of electricity that has the same pattern as wind turbines. WIND can be generated from wind turbines, but also from any other technology if dispatched proportionally to wind turbines.

$$\bar{v}'_{load} = \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{\tau=1}^{\mathrm{T}} l_{t,n,\tau} \cdot v'_{t,n,\tau} \qquad (7)$$

where $l_{t,n,\tau}$ is the share of consumption at the respective time-step, node, and lead time. $\bar{v}'_{load}$ is the consumers' willingness to pay for an additional MWh of yearly consumption that has the same pattern as infra-marginal consumption. [Under perfect and complete markets, $\bar{v}'_{load}$ equals average electricity prices consumers pay, $\bar{p}'_{load}$.] We label the corresponding good LOAD. We will use this good as a reference in the following section.

In general, the generation patterns of any generator are different from load pattern

$$g_{i,t,n,\tau} \neq l_{t,n,\tau} \qquad \forall i \in I \qquad (8)$$

and hence marginal values of a generator does not coincide with the marginal value of load

$$\bar{v}'_i \neq \bar{v}'_{load} \qquad \forall i \in I \qquad (9)$$

[In general, the market value of a technology does not coincide with the average electricity price $\bar{p}'_{load}$.]

The marginal value if a generation technology is a function of many parameters. Specifically, it is typically a downward-sloping function of a technology's total generation q_i

$$\bar{v}'_i = \bar{v}'_i(q_i, \cdot) \qquad \forall i \in I \qquad (10)$$

Typically, as a function of q_i, $\bar{v}'_i$ falls steeper than $\bar{v}'_{load}$. With increasing supply of a good, the marginal value of that good falls quicker than that of an imperfect substitute. This is illustrated in Figure 3.

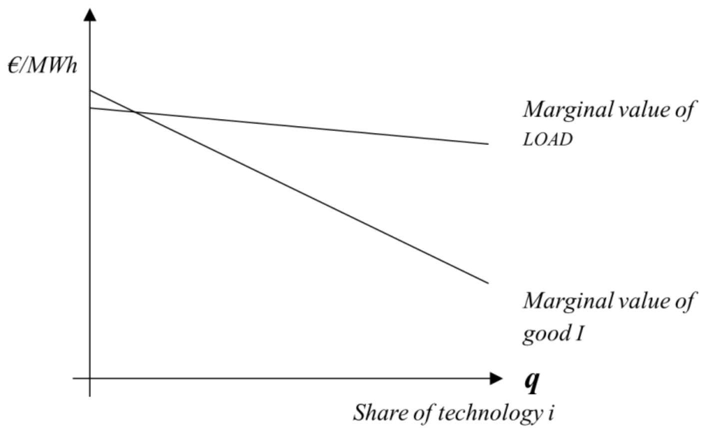

Figure 3: The marginal value of a technology is in general not identical to the marginal value of LOAD. With an increasing market share of i, it declines steeper than $\bar{v}'_{load}$ (illustrative). Source: own work.

Often, the relative value of a technology is of interest. We define the 'value factor' f_i (Stephenson 1973, Hirth 2013a) of technology i as its marginal value over the marginal value of LOAD:

$$f_i = \frac{\bar{v}'_i}{\bar{v}'_{load}} \qquad \forall i \in I \qquad (11)$$

In terms of prices, this is the relative price of electricity from technology i. What Figure 3 displays is that the relative price of good I declines as its supply increases.

We have derived three important results: First, in general different electricity sources have a different marginal value. Second, electricity from different sources is only imperfectly substitutable. Third, in general the marginal value of a generator does not coincide with the marginal value of load. In the following section, we use differences in marginal values to derive a metric that allows comparing the costs of different generators.

4. *System levelized costs of electricity (System LCOE)*

Because the output of different technologies is only imperfectly substitutable, comparing the levelized costs (LCOE) of different technologies does not allow inferring about economic efficiency. However, such comparisons are widespread in academic, policy, and industry documents. Apparently there is a demand to compare technologies in terms of costs. To allow such comparisons in an economic sensible way, we propose the augmented metric *System LCOE.* We have derived System LCOE previously (Ueckerdt et al. 2013a) in a different but equivalent way.

To compare costs, we have to 'transform' different goods (e.g. WIND or COAL) such that they are substitutable – i.e. that their marginal values are the same. We use a 'reference good' that has a specific marginal value; here, we use LOAD. By 'transforming' different goods into the reference good they get the same marginal value. As a result, the costs of generating the reference good from different technologies can be compared to infer about efficiency or competitiveness of each technology.

We define *System LCOE* of technology i as the costs σ_i' (in €/MWh) of generating the reference good from a technology i. These costs are composed of the ordinary generation costs c_i' of that technology and Δ_i' which are the costs of transforming that generation into the reference good:

$$\sigma_i' := c_i' + \Delta_i' \qquad \forall i \in I \qquad (12)$$

More specifically, c_i' are the long-term marginal generation cost of technology i to produce good I. These are the LCOE of i, the discounted average private life-cycle costs of a generator (fixed and variable, including the cost of capital):

$$c_i' = \sum_{y=1}^{Y} \frac{1}{(1+r)^y} \frac{c_{i,y}}{g_{i,y}} \qquad \forall i \in I \qquad (13)$$

where $c_{i,y}$ are the costs that occur in year y, $g_{i,y}$ is the amount of electricity generated in that year, r is the real discount rate, and Y is the life-time of the asset in years. LCOE is a standard concept and widely used. In contrast Δ_i', which will be examined in the following.

Δ_i' depends on the chosen reference good and can be positive or negative. We use LOAD as a reference good, i.e. one MWh of electricity generation that has the same pattern as consumption. This refers to the universal objective of all generating technologies, covering load. Moreover, there are several convenient features of choosing LOAD that we will show in section 5a. The simplest way to supply LOAD can be imagined as a (hypothetical) ideal technology that follows load over time as if it was perfectly dispatchable, has the same spatial distribution, and exhibits the same forecast errors.

The costs Δ_i' are determined by the deviations of a technology's generation pattern from those of the ideal generator (along all three dimensions of heterogeneity). We interpret this mismatch of a technology's generation pattern from load pattern as *variability* of that technology. This provides a definition of variability, a term that is widely used but rarely defined formally. A technology i features no variability if

$$g_{i,t,n,\tau} = l_{t,n,\tau} \qquad \forall t \in T, n \in N, \tau \in \mathrm{T} \qquad (14)$$

Otherwise, it features variability.

As a result, producing LOAD from a generator that is subject to variability has technology-specific *opportunity cost of variability*[10] compared to using the ideal generator. This links variability to Δ_i': The variability cost is the cost Δ_i' of transforming the good I into the good LOAD. Opportunity cost is the gap between the marginal value of a chosen technology and an alternative, which is in our case the ideal generator. We thus identify:

$$\Delta_i' = \bar{v}_{load}' - \bar{v}_i' \qquad \forall i \in I \qquad (15)$$

Recall the definition of System LCOE, equation (12). System LCOE is the sum of generation costs and the value difference between the good that the generator produces and the reference good. This allows interpreting the economic impact of variability in two equivalent ways: costs of variability *decrease the marginal value* or, alternatively, *increase the System LCOE* of a technology (Figure 4). The two concepts allow evaluating a technology from two corresponding perspectives, as we will show in the next section.

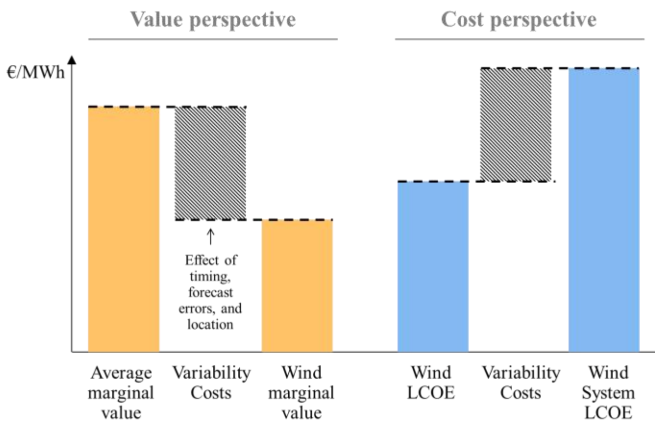

Figure 4: Costs of variability are defined as the difference of the marginal value of a technology compared to that of LOAD (left). System LCOE of a technology are defined as the sum of its LCOE and the costs of variability (right). Source: own illustration

Note that the variability cost of a technology should be understood rather conceptually than technically. It is *not* the cost of locally adding a storage unit close to a wind turbine to smooth fluctuations to better follow load. Instead, variability cost comprises all costs that occur throughout the power system when the output of a technology (e.g. WIND or COAL) is transformed to cover load in a cost-optimal way.

Costs of variability are zero for a technology that perfectly follows load (along all three dimensions). They are positive for technologies with low marginal value and negative for technologies with high marginal value. The generation-weighted sum of the variability cost of all technologies is zero. If electricity was a homogenous good, the marginal values of all technologies would be the same and consequently the cost of variability of all technologies would be zero. Hence, the heterogeneity of electricity is a necessary condition for variability to be costly!

This section discussed that costs of variability *decrease the marginal value* or *increase the System LCOE* of a technology. In the last section we have argued that the relative value of a technology is declining with supply, i.e. the marginal value of a technology is steeper downward sloping than the marginal value of LOAD. Hence, in that sense, variability *causes* the marginal value curve to become steeper (Figure 5). The more variable a technology is (the worse of a substitute it is to load), the more the curve pivots. Analogously, the System LCOE curve of a

[10] For brevity, we use 'variability cost'.

technology emerges from pivoting the marginal costs curve of that technology. Hence, the variability can be understood as reducing value or increasing costs - relative to a technology that is not variable.

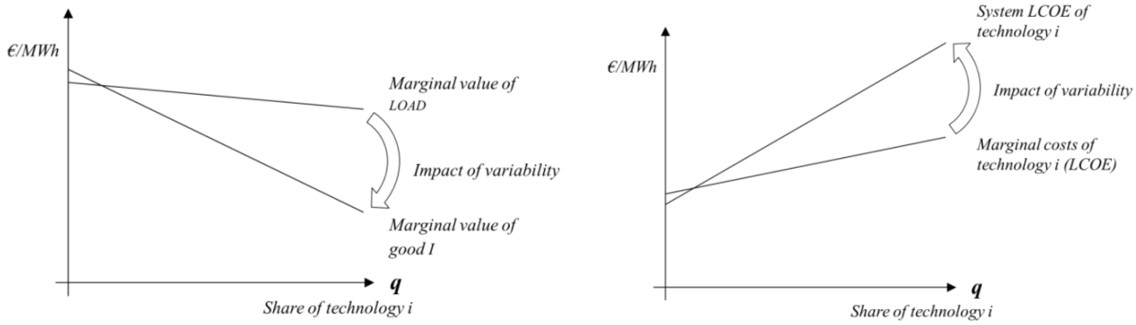

Figure 5: Variability of a technology decreases its marginal value with increasing deployment (left) or analogously pivots its marginal costs curve such that System LCOE of that technology are constructed (right). (figures are illustrative). Source: Own illustration.

This section has established two important results: heterogeneity is a precondition for variability to be costly; and there are (at least) two equivalent perspectives on variability costs. In the next section we use these two perspectives to evaluate technologies by deriving optimality conditions for their welfare-optimal deployment.

5. *The welfare economics of power generation in two perspectives*

This section characterizes the long-term welfare optimum under multi-dimensional heterogeneity. We maximize welfare with respect to the generation mix and derive first-order conditions. We show that the optimum can be expressed equivalently in two ways, a 'technology perspective' that builds on marginal value and a 'load perspective' that builds on variability costs and System LCOE. Each perspective expresses optimality conditions in terms of a different electricity good. We then show that some assessments, like LCOE comparisons, grid parity calculations, and simplistic multi-sector modeling, implicitly confuse these perspectives and equate marginal costs and marginal value of different goods.

Economists and power system models have long ago developed models to derive the optimal capacity mix under heterogeneity. These methodologies explicitly specify the arbitrage constraints that cause heterogeneity (recall section 2), but are often restricted to one-dimensional heterogeneity. For example, a graphical method that uses 'screening curves' and 'load duration curves' has been used for decades to determine the optimal capacity mix (Phillips et al. 1969, Stoughton et al. 1980, Grubb 1991, Stoft 2002, Green 2005); Hirth & Ueckerdt (2013a) use this method but account for exogenous amounts of variable renewables. This optimization technique accounts for temporal heterogeneity of electricity, but requires strong assumptions (no trade, no intertemporal constraints, perfectly price-inelastic demand), optimizes only thermal capacity, and, most importantly in the context of this paper, ignores the other two dimensions of heterogeneity.

To relax these strict assumptions, more complex models have been developed. Such numerically solved 'power market models' have been used at least since the 1960s (Bessiere 1970, Jenkins & Joy 1974, Covarrubias 1979, Martin & Diesendorf 1983) and are currently widespread in academic and industry applications.[11] These models explicitly represent heterogeneity (at least the time dimension) by applying a high resolution and solving the model for each time step individually. Some of these models also represent heterogeneity across space and over lead-time explicitly.

If such explicit modeling of heterogeneity in high-resolution models is feasible, results are unbiased. However, because of complexity or numerics, heterogeneity cannot or is not always be explicitly accounted for. For example, due to numerical constraints, multi-sector models often cannot represent heterogeneity. For (seemingly) intuitive communication, technologies are evaluated in terms of LCOE or 'grid parity', indicators that implicitly assume homogeneity. Also high-resolution models are often restricted to one dimension of heterogeneity and do not model the other two.

In the following, we derive first-order conditions that fully account for heterogeneity. This help understanding why high-resolution methods are required, why low-resolution methodologies are biased, and suggests approaches how heterogeneity can be parameterized in low-resolution tools. The first-order conditions implicitly identify the optimum. For explicit solution and quantifications, high-resolution methods are needed, and this framework is not meant to substitute those.

a) *Optimality conditions*

The optimal quantity q^* of any good is given by the intersection of the marginal economic value (benefit) $v'(q^*)$ of consumption and marginal economic cost $c'(q)$ of production. This is the well-known and standard first-order condition for the welfare optimum:

$$v'(q^*) = c'(q^*) \tag{16}$$

Condition (16) obviously only makes sense if marginal value and marginal cost of *the same good* are compared. While this sounds like a trivial statement, in the electricity sector it is not – as each technology produces a different good. Many analyses implicitly compare the benefit and cost of different goods, for example if LCOEs of different technologies are compared, if the LCOE of a technology is compared to the average electricity prices[12], or if multi-sector models specify only one single electricity price. Such confounded analyses results in biased findings and flawed conclusions. As Figure 6 illustrates, equating the LCOE of a technology with the average electricity price results in the quantity q_i^0, which is not the optimal quantity q_i^*. To derive that optimal quantity, one needs to frame the analysis *either* in terms of the good that the respective technology produces, I, *or* the good LOAD. We call the former the 'technology perspective' and the latter the 'load perspective'.

In the following we assume consumption to be given[13] and cost and welfare functions to be well-behaved. We first derive the first-order conditions in the 'technology perspective', similar to Hirth (2013a). The quantity q_i of electricity generation technology i is optimal if the marginal value of the good that i produces coincides with marginal cost of production. This can be expressed in marginal value and marginal costs of the good I:

$$\bar{v}_i'(q_i^*,\cdot) = c_i'(q_i^*,\cdot) \qquad \forall i \in I \tag{17}$$

[11] A few examples that apply power market models for questions related to variable renewables and their variability include Swider & Weber 2006, Lamont 2008, 2012, Neuhoff et al. 2008, Lamont 2008, Fripp and Wiser 2008, Möst & Fichtner 2010, Nagl et al. 2011, 2012, Mills & Wiser 2012, 2013, Nicolosi 2012, Hirth 2013a, 2013b, and Müsgens 2013.

[12] Under perfect and complete markets, this equals the marginal value of load.

[13] The (yearly) consumption level is relatively straightforward to endogenize.

where $\bar{v}_i'$ is the marginal value of good I and c_i' is the marginal cost of producing good I with technology i, that is the LCOE of i. Together, these I first-order conditions implicitly determine the optimal generation mix. Because of electricity's heterogeneity, there are typically millions of constraints, hence an explicit solution can only be determined numerically; see Hirth (2014) for a numerical application with explicit solutions. In this perspective, the variability of generator i affects its marginal value, hence it might also be called the 'value perspective'.

Alternatively, the same optimality conditions can also be expressed marginal value and marginal costs of the good LOAD. This is the 'load perspective', as taken by Ueckerdt et al. (2013a):

$$\bar{v}_{load}'(q_i^*,\cdot) = \sigma_i'(q_i^*,\cdot) \qquad \forall i \in I \qquad (18)$$

where $\bar{v}_{load}'$ is the marginal value of good LOAD and σ_i' is the marginal cost of producing good LOAD with technology i, that is the System LCOE of i. In this perspective, the variability of generator i impacts its marginal cost, hence it might also be called the 'cost perspective'. Because the marginal value of good LOAD is the same across technologies, this set of I first-order conditions can conveniently be expressed as equalities between System LCOEs:

$$\sigma_i'(q_i^*,\cdot) = \sigma_j'(q_j^*,\cdot) \qquad \forall i,j \in I \qquad (19)$$

The optimality condition for quantity q_i^* can be written in terms of the good the respective technology produces, I, (17) or in terms of the good LOAD (18). This duality can be neatly illustrated graphically (Figure 6). The 'technology perspective' is depicted in bold lines. The intersection of marginal costs (LCOE) and marginal value of I gives the optimal quantity q_i^*. The 'load perspective' is drawn in dotted lines. The intersection of marginal costs (System LCOE) and marginal value of LOAD results in the same optimal quantity q_i^*. However, the intersection of marginal value of LOAD with the marginal costs of technology I gives quantity q_i^0, which is *not* the optimal quantity.

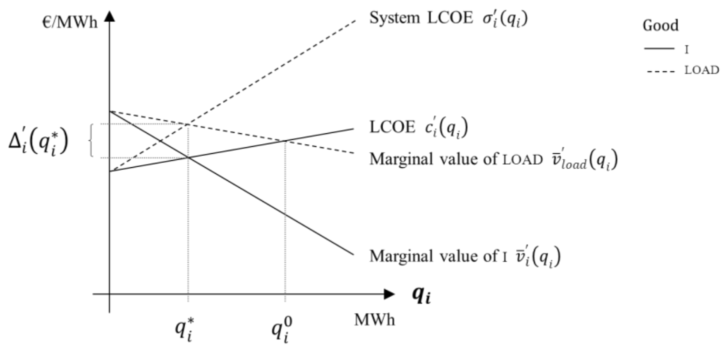

Figure 6: Optimal quantity q_i^* of technology i in terms of the goods I (technology perspective) and LOAD (load perspective).

Figure 6 assess the optimal quantity of one technology. Now we turn to the global optimum where all technologies are deployed optimally. Figure 7 displays such an optimum in the 'technology perspective'. The marginal cost of each technology coincides with the marginal value of the good it produces. In general, the marginal value of each technology is different. Figure 8 expresses the same in the 'load perspective'. Here, the System LCOEs of all technologies coincide. In both cases, differences in LCOEs do not indicate suboptimality.

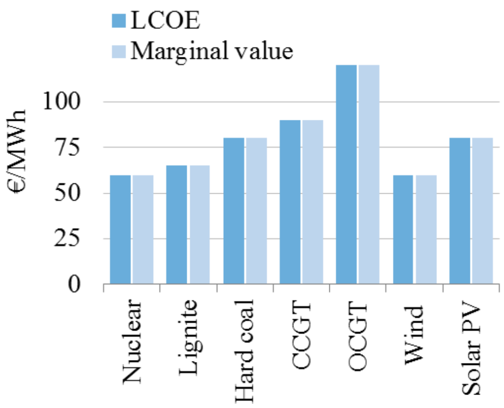

Figure 7: The welfare optimum in the 'technology perspective'. The marginal value of each technology coincides with its marginal costs.

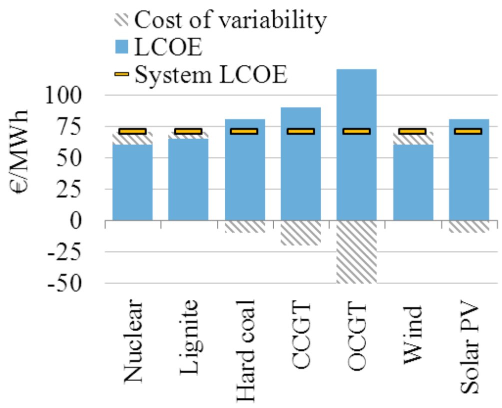

Figure 8: The welfare optimum in the 'load perspective'. All System LCOEs coincide.

Some analysts find one perspective more intuitive and appealing, while others prefer the other. The discussion concerning variable renewables is an example: energy traders and economists often prefer to think of variability decreasing the value of wind and solar power. They often find the 'technology perspective' to be quite natural. System operators, policy makers, modelers, and power system engineers often strive to understand the 'cost' of variability and hence prefer the 'load perspective'. We see three broad applications of the 'load perspective' and the corresponding concept of System LCOE:

1. Some IAMs represent VRE variability as cost penalty. System LCOE can improve these approaches by providing a rigorous welfare economic motivation and parameterization (section 7a).
2. Practitioners and academics frequently compare power-generating technologies in terms of LCOE, in particular to infer about their competitiveness. Apparently authors appreciate the (apparently) straightforward communication that LCOE comparisons allow. System LCOE can replace the flawed metric of LCOE.
3. The 'integration cost' literature assesses the cost of wind and solar variability. System LCOE connects this literature branch with the economic literature on marginal value and hereby provides a welfare-economic interpretation of integration cost estimates (section 7d).

Our contribution to this debate is to point out that both perspective, if applied consistently, are equivalent.[14]

We have expressed optimality conditions for the social planner solution. If markets are perfect and complete, welfare optimality corresponds to the long-term equilibrium, and marginal values and costs correspond to prices. The results do not require perfect and complete markets; however, some findings can be expressed more elegantly in terms of prices. The instantaneous marginal value , $v'_{t,n,\tau}$ equals the locational spot price $p_{t,n,\tau}$. The marginal value space (Figure 1) corresponds to a matrix of spot prices. The marginal value of LOAD, $\bar{v}'_{load}$, is the electricity price $\bar{p}_{load}$ that consumers pay on average. We call $\bar{p}_{load}$ the 'average electricity price'. The marginal

[14] In principle, the optimality condition can be formulated from other perspectives by using a different reference good. If specified consistently, this delivers the correct optimal quantity of all technologies. However, choosing LOAD as reference offers a number of more fundamental economic interpretations. First, the marginal value of LOAD is the marginal costs of (proportionally) increasing demand. Second, if markets are perfect and complete, $\bar{v}'_{load}$ is the price that consumers on average pay for electricity. Third, if long-term marginal supply curves are constant, $\bar{v}'_{load}$ equals the average system cost. Fourth, the specific costs of the residual system remain constant in long term when increasing the supply of LOAD.

value of a generator, $\bar{v}_i'$, is its specific average revenue or 'market value' (Joskow 2011, Hirth 2013a).

b) Implications for indicators and multi-sector models

The two perspectives on optimality help to interpret commonly used indicators in an economically sound way, such as LCOEs, 'grid parity', 'capacity credit' and 'curtailment'. These tools and assessment often ignore heterogeneity and, implicitly, confound different economic goods. As a consequence, they derive biased results and find suboptimal quantities that would, if implemented, cause dead-weight loss. For example, in Figure 9 LCOE of a technology are mistakenly compared with the marginal value of LOAD to infer about some (biased) optimal quantity q_i^0. This neglects electricity's heterogeneity and would lead to a welfare loss indicated by the shaded area since the unbiased optimal quantity is q_i^*, which can be derived from a 'technology perspective' (Figure 9, left) or a 'load perspective' (right).

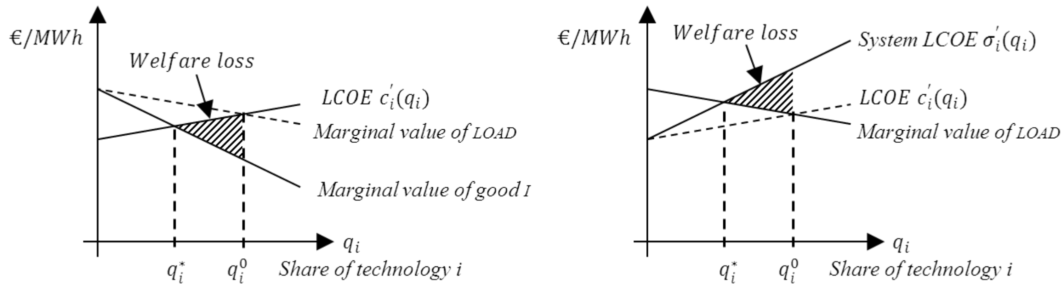

Figure 9: Neglecting electricity's heterogeneity imposes the same welfare loss (shaded area) in the two perspectives 'technology' (left) and 'load' (right).

Often, academic, policy, and industry documents compare the LCOEs of different technologies, implicitly or explicitly suggesting that a lower LCOE indicates efficiency or competitiveness (Karlynn & Schwabe 2009, Fischedick et al. 2011, IEA/NEA 2011, EPIA 2011, DLR et al. 2011, IRENA 2012, Clover 2013, EIA 2013). As equation (17) and Figure 7 show, this is not the case. In fact, comparing LCOEs from different technologies has quite little economic meaning at all, since marginal costs of producing different economic goods are compared. Our analysis suggests a remedy: if technologies are to be compared in terms of per-unit costs, System LCOE should be used. This allows inference on competitiveness and efficiency.

Similarly, it is quite common to compare a technology's LCOE to the average wholesale electricity price, especially for renewables (Kost et al. 2012, Clover 2013). This implicitly compares the marginal cost of producing one good with the marginal benefit of another good, and in general delivers biased results (Figure 3). Our analysis suggests to either compare the LCOE to the market value of the respective good (17), or to compare the System LCOE to the average electricity price (18).

Some authors seem to suggest that once a technology has reached 'grid parity', its deployment is economically efficient (BSW 2011, EPIA 2011, Koch 2013, Fraunhofer ISE 2013, Breyer & Gerlach 2013). Grid parity is usually defined as the point where LCOE of wind or solar power fall below the retail electricity price, sometimes differentiated by type of consumers. Again, this indicators ignores heterogeneity, and implicitly compares value and cost of different goods. Furthermore, 'grid parity' conceals the fact that grid fees, levies, taxes comprise a large share of retail prices. Hence it takes a private perspective that has little implication for social efficiency (Hirth 2014b).

'Capacity credit' is often defined as the share of installed capacity that can be regarded as 'firm', or permanently available (Perez et al. 2008, Ensslin et al 2008, Amelin 2009, Keane et al. 2011, Sims et al. 2011, Holttinen et al. 2011, Madaeni et al. 2012). While this metric might be relevant for system operators to estimate the demand for peak generation capacity, it is an incomplete indicator for welfare analysis. In our framework, a small capacity credit is reflected in the fact that such technologies receive low income during times of scarcity; hence have a lower marginal value. However, while our assessment accounts for all variability, capacity credit only assesses extreme situations such as the hour of the year with highest demand, and ignores heterogeneity along space and lead-time altogether. For example, it is wrong to infer that a technology with zero capacity credit has zero (or low) economic value.

'Curtailment' is the amount of VRE that a power system cannot accommodate. Some studies seek to minimize 'curtailment' when optimizing the deployment of variable renewables and integration measures like storage and transmission grids (Heide et al. 2010, Bode 2013). However, an economic evaluation needs to consider costs. Minimizing curtailment implicitly assumes VRE generation to have infinite value.

Economists have used calibrated multi-sector models for many years for research and policy advice (Leontief 1941, Johansen 1960, Taylor & Black 1974). Numerical constraints often require multi-sector models to model electricity as any other sector and calculate *one* marginal value (the marginal value of LOAD, $\bar{v}'_{load}$). This implicitly assumes that electricity is homogeneous. We have shown that this is a wrong assumption that causes results to be biased (Figure 9). We discuss how System LCOE can be used to correct this bias and to improve the representation of VRE in section 7b.

Ignoring heterogeneity introduces a bias that can be large. The bias is largest for technologies that have a marginal value quite different from LOAD: peaking plants and storage devices that have a high marginal value; and variable renewables at high deployment rates, which have a low marginal value. We will present a meta-analysis of wind variability costs in section 7d that shows that at 30% penetration, wind power's value is about 20-50% below that of LOAD.

We have pointed out the potential flaws of commonly used tools and suggest a number of remedies: cost-benefit assessments require comparing the marginal costs of a generator to its marginal value; technologies can be compared in terms of costs, if System LCOE is used as a metric; multi-sector models should parameterize heterogeneity and/or iterate with high-resolution models. Other indicators, including grid parity, capacity credit, and curtailment, are recommended not to be used for economic assessment.

6. *The components of variability*

Sections 2-5 (implicitly) assumed that the full marginal value space is known. To estimate the complete three-dimensional matrix of marginal values, one needs a 'super model' that fully captures the arbitrage constraints on all dimensions of heterogeneity. In reality, such a model does not exist. For quantitative estimations, one regularly has to rely on estimates from specialized models that represent one or two dimensions of heterogeneity. Acknowledging such imperfect knowledge, we propose to assess the cost of each heterogeneity dimension separately and add up these cost components. This is a pragmatic and operationable approach to estimate marginal value and variability cost. This section formalizes and expands Hirth et al. (2013).

We believe it is intuitive to decompose variability along the dimensions of heterogeneity. Moreover, this facilitates empirical estimation, and allows comparing different aspects of VRE variability economically.

a) A decomposition along the dimensions of heterogeneity

Many models represent only one or two dimensions of heterogeneity. A ‘super model’ that fully represents all heterogeneity dimensions would need to have a high temporal resolution, include the transmission grid, and account for uncertainty. Such a model does not exist, and it might be impossible to construct. In fact, many published studies focus on the impact of one dimension on one technology (like ‘the costs of wind forecast errors’). In the context of such incomplete knowledge, we propose a pragmatic approximation approach: estimating the impact of each dimension separately and adding them up. The impact of the temporal generation profile on the value of electricity is called ‘profile costs’, the impact of locational grid constraints ‘grid-related costs’, and the impact of lead-time ‘balancing costs’. We use the sum of the three components as an estimator $\hat{\Delta}_i'$ for the cost of variability

$$\hat{\Delta}_i' = \Delta_i^{profile} + \Delta_i^{grid\text{-}related} + \Delta_i^{balancing} \qquad \forall i \in I \qquad (20)$$

and as an estimator $\hat{\bar{v}}_i'$ of the marginal value

$$\hat{\bar{v}}_i' = \hat{\bar{v}}_{load}' - \hat{\Delta}_i' \qquad \forall i \in I \qquad (21)$$

$\hat{\Delta}_i'$ is only an approximation of the variability costs Δ_i'. The three cost components interact with each other and there is an (unknown) interaction term $\hat{\varphi}_i$.

$$\Delta_i' = \hat{\Delta}_i' + \hat{\varphi}_i \qquad \forall i \in I \qquad (22)$$

However, lacking knowledge of the sign of the interaction, we believe setting $\hat{\varphi}_i$ to zero it is a sensible first-order approximation. We define profile costs for the situation that only information about the temporal structure of the marginal value of electricity is known, hence $v_{t,n,\tau}'$ reduces to v_t'. Profile costs $\Delta_i^{profile}$ of technology i are defined as the difference between the load-weighted and the generation-weighted marginal value

$$\Delta_i^{profile} := \sum_{t=1}^{T} \left(l_t - g_{i,t}\right) \cdot v_t' \qquad \forall i \in I \qquad (23)$$

We define grid-related costs and balancing costs accordingly:

$$\Delta_i^{grid\text{-}related} := \sum_{n=1}^{N} \left(l_n - g_{i,n}\right) \cdot v_n' \qquad \forall i \in I \qquad (24)$$

$$\Delta_i^{balancing} := \sum_{\tau=1}^{\mathrm{T}} \left(l_\tau - g_{i,\tau}\right) \cdot v_\tau' \qquad \forall i \in I \qquad (25)$$

As variability costs, the three cost components are defined as a *reduction* of marginal value of the good I relative to LOAD.

As an illustrative example, assume one needs to assess the marginal value of WIND in Germany at some point in the future. Say, there is a power market model available that delivers estimates for the marginal value of LOAD of 70 €/MWh and WIND of 60 €/MWh, but that model does not capture the grid, nor does it capture uncertainty - hence does not account for the second and the third dimension of heterogeneity. From a literature review, one estimates balancing costs (the cost of wind forecast errors) to be 3 €/MWh. Finally, a grid study reports the marginal value of electricity in Northern Germany to be 6 €/MWh higher in the South than in the North , and it is known that two thirds of all turbines are located in the North while two thirds of consumption in the South. Hence, profile costs are 10 €/MWh, balancing costs 3 €/MWh, and grid-related costs 2 €/MWh.[15] In sum, the marginal value of WIND is $\hat{\bar{v}}'_{wind} = 55\,€/MWh$, and the variability cost of wind power $\hat{\Delta}'_{wind} = 15\,€/MWh$.

In the following, we use waterfall diagrams to illustrate the impact of the three variability components on the marginal value of electricity goods. Base load generators like nuclear power have a lower value than LOAD, hence they feature positive variability costs (Figure 10a). Mid-term generators like coal-fired plants have a value that is close to that of LOAD (Figure 10b). Flexible peak load generators that are located close to load centers have a high value (Figure 10c) They benefit from producing during times of high value, from providing flexibility after unexpected events, and from being located at high-value locations - hence all cost components increase their marginal value. The value of VRE is strongly affected by their penetration. At low shares, their value is typically higher than LOAD, especially the value of SOLAR (Figure 10d). Solar's value is high, because solar radiation is positively correlated with the temporal structure of demand; this effect is larger than the cost of forecast errors that reduce the value. At high penetration, profile, balancing, and grid related costs reduce the value both of SOLAR and WIND (Figure 10e).

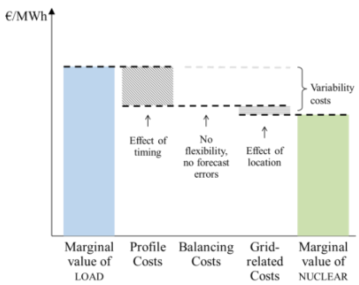

Figure 10a: The marginal value of NUCLEAR (illustrative).

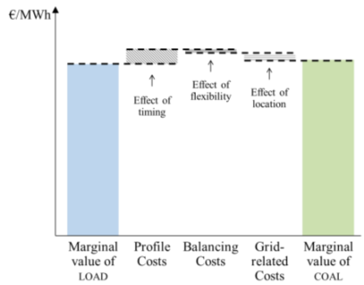

Figure 10b: The marginal value of COAL at high penetration (illustrative). As a mid-merit plant, the temporal pattern increases its value somewhat. Forecast errors and location have little impact. Variability costs are close to zero.

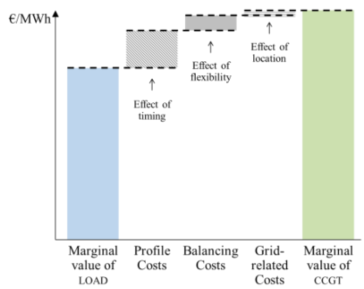

Figure 10c: The marginal value of CCGT (illustrative). As a peaking plant, the temporal pattern increases its value significantly. Flexibility and location increase the value. Variability costs are negative (increase the value).

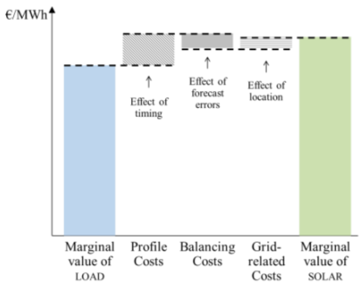

Figure 10d: The marginal value of SOLAR at low penetration (illustrative).

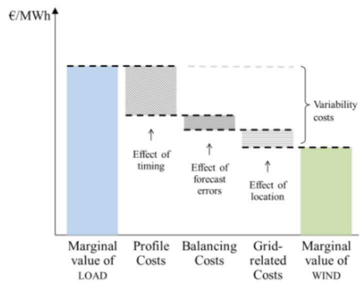

Figure 10e: The marginal value of WIND at high penetration (illustrative). Timing, forecast errors, and remote location decrease the marginal value. Variability costs are positive.

The three cost components, profile, balancing, and grid-related costs, are not constant parameters, but functions of many system parameters. Especially, they typically increase with penetration as illustrated in Figure 11 and shown in the quantifications of section 7d.

[15] Grid-related costs are the spread between the load-weighted and the wind-weighted electricity price: $\frac{12}{3} - \frac{6}{3} = 2$

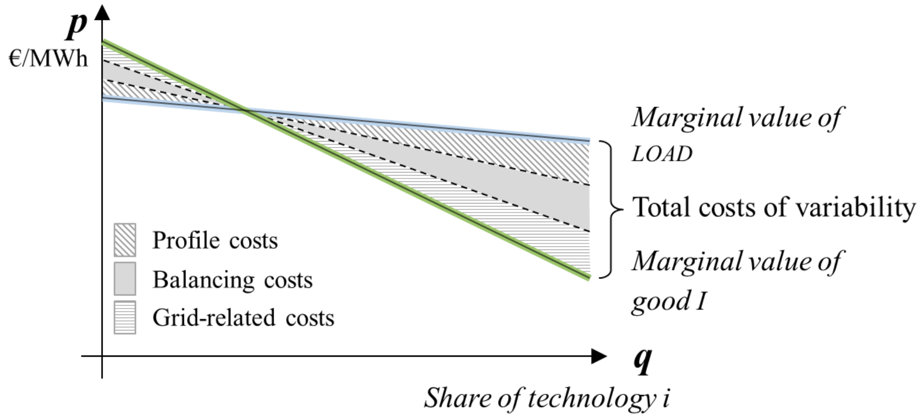

Figure 11: Profile, balancing, and grid-related costs typically increase with penetration. For wind and solar power, profile costs are often negative at low penetration, increasing their value above the value of LOAD.

b) *Quantifications from models and markets*

An important merit of our definition of variability costs and the three cost components is that they can be quantified from *models and markets*: estimates of each cost component can be derived from modeled shadow prices or observed market-clearing prices. Both approaches have their limitations: markets are never perfect and free of market failures and can be, in the case of electricity, quite far away from the equilibrium for extended periods of time (section 7c). Models are necessarily simplifications of reality, many externalities are only incompletely captured, some models do not estimate the long-term equilibrium, and numerical models are often calibrated to historical market prices anyway. While both model- and market-based estimation has their limitations, such diversified quantification methodologies allow for more robust estimates.

Models are often specialized in the sense that they represent one dimension of variability (much) better than others. For empirical market design a similar argument holds: a certain market (say, Germany) might represent temporal heterogeneity well, lead-time heterogeneity less well, and locational heterogeneity not at all. Hence both model and market-based estimates will often deliver only estimates of the individual cost components profile, balancing, or grid-related costs. The decomposition of variability costs into three components also allows to combine model-based with market-based estimates.

Profile costs can be readily estimated from power market models as the ones mentioned in section 5. Balancing costs can be estimated from stochastic unit commitment models that explicitly model unexpected events and the constraints on ramping and start-up of thermal generators. Grid-related costs can be estimated from load flow models that explicitly represent the transmission network and Kirchhoff's laws.

Naturally, market prices can be observed only in liberalized markets. Different segments of the wholesale market provide price information regarding different dimensions of heterogeneity. Profile costs can be estimated from day-ahead spot markets. Spot market prices are readily available from power exchanges or ISOs in almost all liberalized markets. Grid-related costs can be estimated from locational market prices. Such prices include locational (zonal or nodal) marginal spot prices, as in many U.S. and Australian markets, and/or locational grid fees, as in Sweden. Some markets, such as many European markets, do not price grid constraints at all, hence no market data can be used to estimate grid-related costs. Balancing costs appear in different forms: intra-day spot market prices, the price that system operators pay for balancing services (balancing power prices), and the price that actors have to pay for forecast errors (imbalance prices).

We define the market value $\tilde{v}_i'$ of technology i as its specific income from spot markets. The tilde accent indicates its origin from estimated from observed market or modelled shadow prices $\tilde{p}_{t,n,\tau}$

$$\tilde{v}_i' = \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{\tau=1}^{\mathrm{T}} g_{i,t,n,\tau} \cdot \tilde{p}_{t,n,\tau} \qquad \forall i \in I \qquad (26)$$

Analogously, one can estimate profile costs from empirical prices

$$\tilde{\Delta}_i^{profile} := \sum_{t=1}^{T} (l_t - g_{i,t}) \cdot p_t \qquad \forall i \in I \qquad (27)$$

and balancing and grid-related costs can be estimated accordingly.

$\hat{\tilde{\Delta}}_i'$, the cost of variability as derived from individual cost components if those components are derived from empirical prices can be used as an estimator for Δ_i'

$$\Delta_i' = \hat{\tilde{\Delta}}_i' + \tilde{\varphi}_i + \hat{\varphi}_i \qquad \forall i \in I \qquad (28)$$

However, two errors are introduced: an error $\tilde{\varphi}_i$ stemming from the fact that markets and models are imperfect, incomplete, and out-of equilibrium; and an error $\hat{\varphi}_i$ stemming from the fact that we add components without considering interactions.

c) *Three characteristics of VRE*

Heterogeneity applies to electricity per se, all generators are subject to variability costs, and each technology's variability cost can be decomposed into components. However, in the case of VRE there is another benefit of such a decomposition: each component corresponds to a specific characteristic of VRE.

Previous studies have identified three inherent properties of wind and solar power: (temporal) variability, forecast errors, and the fact that they are bound to certain locations (Milligan et al. 2011, Borenstein 2012). The economic impact of these properties has been assessed, but such assessments has lacked welfare-economic interpretation (Sims et al. 2011, IEA 2011, see also section 7b). VRE's three properties correspond to the three dimensions of electricity's heterogeneity (Table 3).

Table 3: The heterogeneity of electricity and the properties of VRE.

Dimension	Time	Space	Lead-time
Property of VRE	Temporal variability	Bound to certain locations (land availability, resource quality)	Forecast errors
Cost component	Profile costs	Grid-related costs	Balancing costs

As a consequence, our decomposition allows evaluating the properties VRE economically. Temporal variability, network constraints, and forecast errors can be consistently compared and monetarized. For example, the profile costs of wind, the opportunity costs of wind's temporal variability, can be compared to the balancing costs of wind, the opportunity costs of wind's limited predictability. This might lead to surprising insights: as we report in section 7d, in the case of wind power, forecast errors have received much attention in the public and academic debate on ‘intermittency’. However, profile costs at high penetration can be several times large than balancing costs.

Putting these characteristics in the context of the framework of this paper also clarifies that VRE variability, location, and forecast errors alone do not cause any costs. Only because electricity is heterogeneous, these properties of VRE have any economic impact.

7. The economics of wind and solar variability

Heterogeneity is a property of electricity itself, and all technologies are subject to variability. However, many authors, including ourselves, have labelled wind and solar power as ‘variable’ or ‘intermittent’ power sources and emphasized differences to ‘dispatchable’ generators. In fact, there exists a vast literature that discusses the economics of VRE variability – IEA (2014) provides an excellent overview. Indeed, there is a good reason to pay specific attention on wind and solar power variability: at high penetration rates (maybe >20% wind or >10% solar share in energy terms), those technologies might have the lowest marginal value of all generators - hence ignoring heterogeneity introduces the largest upward bias. This section focuses on VRE.

We relate three branches of the literature on VRE variability to the framework developed in this paper. In section 7a), we discuss how VRE can be modeled in multi-sector models. Especially the IAM community has discussed intensively how to model wind and solar variability. We hope that the concept of System LCOE can help addressing this challenge. In section 7b), we discuss the literature on ‘integration costs’ and the relation between integration costs and the welfare economics of electricity under heterogeneity. Specifically, we propose a new definition of integration costs. In section 7c, we discuss how power systems adopt if large volumes of VRE are deployed. Such adaptations significantly impact quantitative estimates, as we report in section 7d), where we extract cost estimates from a large number of published studies.

a) Representing variability in multi-sector models

For many years, academics have used calibrated multi-sector models for policy advice. For long-term assessments of climate policy and global change, ‘integrated assessment models’ (IAMs) find widespread applications. Such IAMs represent the entire world economy and find intertemporal optima over decades or centuries. They can capture important aspects of optimal VRE deployment, such as technological learning, endogenous fuel and CO_2 prices, and general equilibrium effects. Model intercomparison projects regularly find VRE to grow dramatically, especially, but not only, under strict climate policy (Fischedick et al. 2011, Edenhofer et al. 2013, Knopf et al. 2013). The electricity sector generally and VRE specifically are often regarded as a major greenhouse gas mitigation option. However, there is widespread agreement that appropriately accounting for VRE variability is a major challenge to IAM modeling (Luderer et al. 2013, Baker et al. 2013). While *all* generators are subject to variability, we focus here on VRE, because there is a rich academic debate around them.

Due to numerical constraints, IAMs cannot provide the temporal and spatial resolution required to explicitly represent the heterogeneity of electricity. Their typical time resolution is in steps of 5–10 years and model regions as large as Europe as a whole. Many models use stylized formulations to account for variability, however, most of these approaches lack welfare-theoretical rigor. As a consequence, these approximations reduce the robustness of model results and increase the uncertainty in estimating the optimal deployment of VRE. In particular, ignoring variability underestimates the costs of VRE in the electricity sector, especially at high penetration rates. While some models – mostly older versions of IAMs – ignore variability altogether and thus generate results that are biased towards optimistic cost estimates, today most IAMs apply some sort of stylized formulation to represent the challenges of variability. Of the 17 models reviewed by Luderer et al. (2013), two ignore variability; the others limit the maximum share of variable renewables (seven models), require dedicated storage or back-up capacity (eight models), or add a cost penalty (four models: MERGE, MESSAGE, ReMIND, and WITCH). The most basic approach is to set a hard limit to the generation share of wind and solar. However, this implicitly assumes zero marginal value at higher shares, which is an extreme assumption. Such hard constraints are price-insensitive and ignore the possibility for system adjustments even under strong economic pressure. A more economic approach is to introduce an 'integration cost penalty' that might increase with its penetration. Other models require the provision of specific technology options to foster the integration of VRE, like gas-fired backup capacities or electricity storage. Six models models represent load variability with a load duration curve. Sullivan et al. (2013) propose a 'flexibility constraint' to account for variability. However, all these approaches have three limitations. First, the foundations and completeness of the approaches is unclear. Often motivated from a technical perspective, they lack a clear relation to the economic costs of variability. Second, each approach focuses on specific aspects of variability while omitting others. Finally, these stylized representations are difficult to parameterize.

The discussion of heterogeneity and marginal value of different generators helps clarifying the challenges to IAM modelers: it is not only VRE variability that is problematic for low-resolution models, but the entire electricity sector. In the following, we discuss possibilities to use the concepts of System LCOE in addressing these caveats.

Using (12), the optimality condition (18) can be rearranged specify the optimal quantity of a VRE technology, for example wind power:

$$\bar{v}'_{load}(q^*_{wind},\cdot) = c'_{wind}(q^*_{wind},\cdot) + \Delta'_{wind}(q^*_{wind},\cdot) \tag{29}$$

This condition can be interpreted as the following: IAMs, which perform their analysis at a coarse resolution and in terms of the good LOAD, have to amend the marginal costs of WIND with a cost mark-up. This cost mark-up, which we have termed variability costs Δ'_{wind}, is the difference in marginal benefit of two economic electricity goods, the good that IAMs are specified in (LOAD) and the good that wind turbines supply (WIND). In the context of IAMs, LOAD is a sensible reference good, because it is the average price consumers pay and hence the turnover of the sector can be calculated as 'price times quantity'.

The framework developed in sections 2-6 can help to improve the representation of variability in IAMs. First and foremost, it is not VRE's variability per se that provides the methodological challenge, but only in conjunction with the heterogeneity of electricity. Not only renewables, but *all* power generation technologies need to be modelled in a way that accounts for their different marginal value. Second, IAM development should prioritize those aspects that have the largest impact on model results, which are often profile costs (see Section 7d). Third, to estimate variability cost, tools other than IAMs are needed, such as high-resolution numerical or econometrical models. From such models, System LCOE can be estimated and implemented to IAMs to represent variability. That would give the common method of using cost-penalties for VRE a rigorous welfare-economic foundation. However, System LCOE $\Delta'_i(q^*_i,\cdot)$ is system-specific by definition and its ex-ante calculation with a partial model might not be the same across regions and scenarios. Consequently, it could be estimated on a regional basis and model results should be iterated. To reduce the need for such an iterative model coupling, where possible, some aspects of variability could be modeled explicitly in IAMs. For instance, endogenous residual load duration curves could address a large part of profile costs (Ueckerdt et al. 2011). More detailed aspects like grid-related and balancing costs could be implemented by adding a reduced-form formulation of System LCOE. A sound representation of variability would likely be a model-specific combination of different explicit and implicit elements.

b) A new definition of integration costs

Quite unrelated to the IAM literature, there exists an establish branch of literature that seeks to calculate 'integration costs' of VRE.[16] Integration costs have been defined as "the extra investment and operational cost of the nonwind part of the power system when wind power is integrated" (Holttinen et al. 2011) or "the additional cost of accommodating wind and solar" (Milligan et al. 2011). In particular integration studies have sought to operationalize and to quantify those costs with high-resolution production cost modeling techniques (Gross et al. 2006, Smith et al. 2009, GE Energy 2010). Those studies often decompose integration costs into 'balancing', 'grid', and 'adequacy' costs. However, the economic interpretation of integration costs remains somewhat opaque.

In line with NEA (2012), Milligan et al. (2013) reports that integration costs are interpreted and used in several ways. Readers "add the integration cost to the cost of energy from wind power to provide a comparison of wind energy to a more dispatchable technology". We assume they do so to assess competitiveness and efficiency. This interpretation offers a link to the framework of this paper: inference about competitiveness and efficiency is only possible if integration cost is defined as variability cost.

Hence, we follow Hirth et al. (2013) and Ueckerdt et al. (2013a) and propose to define integration costs of a technology as 'the difference in marginal value between load and the electricity good that the respective technology produces' - exactly as variability costs were defined in (15). With that definition, the sum of generation and integration cost is System LCOE, a metric that indeed allows inference about competitiveness and efficiency from technology comparisons.

There are three fundamental differences between the 'classical' and this definition of integration costs: First, this definition is defined in marginal terms, while classical definitions are often calculated in average terms. Second, this definition is more comprehensive in the sense that it includes differences in the 'energy value', i.e. profile costs. Ueckerdt et al. (2013b) point out that classical definitions capture only the cost increase of other generators, while a marginal value-based definition also captures reduced cost savings. Ueckerdt et al. propose to call the former "integration costs in a narrow sense". Finally, the integration cost literature often uses static models without much system adaptation. Assumptions on time horizon and system adaptation can greatly impact model estimates.

c) Time horizon and system adaptation

The marginal value of wind and solar power, and hence their variability cost, System LCOE, and optimal deployment, depends not only on the variability itself, but also on many parameters of the residual power system: the thermal capacity mix, the transmission grid, market design, and much more. When quantifying the economic impact of high shares of wind and solar power, studies take very different assumptions about the ability of the power system to adapt to the introduction of large quantities of VRE. In general, integration costs and System LCOE can be

[16] The 'IEA wind task 25' is the most important forum where integration cost methodology is discussed and developed.

expected to decrease if the power system is allowed to adapt in response to increasing VRE penetration. Similarly, the marginal value can be expected to increase due to system adaptation.

Power systems can adapt in a multitude of ways to increasing VRE penetration. The following list of adaptations is roughly ordered by increasing time that is needed: Operational routines and procedures can be changed; market design can adopt; existing assets can be modified to operate more flexibly or under otherwise changed conditions; the capacity mix can shift; the transmission grid can adjust; technological innovations can take place like integration options (Hirth & Ueckerdt 2013b). The reason for changes to take time is inertia, for example the sunk investments in physical capital. Since life-time of physical assets is long, power systems can be out of equilibrium for extended periods of time after the swift introduction of significant amounts of VRE.

How much the marginal value differs between a not adapted and an adapted system depends on three factors: the system's adaptation potential; the speed of system adaptations; and the speed of VRE deployment. For example, if VRE is introduced very slowly relative to the natural rate of turnover of the power system, the system might remain constantly perfectly adapted during the transformation process. If VRE are rapidly introduced to a power system that features many long-living base load plants, integration cost can be quite high (Ueckerdt et al. 2013b).

Any analysis should be explicit about the temporal perspective applied and be aware about its effect on the results. System adaptation can significantly ease the integration of VRE and consequently short-term cost estimates should be treated with care. This can be seen in the next section where we quantify integration costs from a literature review.

d) Quantification

A key merit of this framework is that integration costs can be quantified, both from market (price) data or model (shadow price) estimates. In the following, we survey the quantitative literature and extract estimates for profile, balancing, and grid-related costs. Since the field lacks both a common terminology and consistent methodologies, results cannot be readily take from studies but had to be translated.

Profile cost estimates can be extracted from a large number of studies. Grubb (1991) provides an early quantification of profile costs. Lamont (2008), Mills and Wiser (2012), Nicolosi (2012a), and Hirth (2013a) provide recent estimates based on calibrated numerical models. Profile costs can be readily observed on wholesale power markets. For example, in 2001, when wind power had a market share of 2% in Germany, the average income of wind power on the day-ahead spot market was only 2% below the load-weighted price - in 2012, when the market share had risen to 8%, the gap had increased to 13%. Fripp and Wiser (2008) report comparable figures for California.

Balancing costs are assessed by a similar number of studies. Holttinen et al. (2011) provides a recent survey of integration studies and Gowrisankaran et al. (2011) and Mills and Wiser (2012) provide high-quality model estimates. Holttinen (2005), Pinson et al. (2007), Obersteiner et al. (2010), and Holttinen & Koreneff (2012) provide estimates from market data. However, Hirth & Ziegenhagen (2013) identify externalities in balancing markets, indicating that the economic robustness of market price estimates is doubtful.

Hirth et al. (2013) review these and more studies in detail. Figure 10 and Figure 11 summarize estimates of profile costs and balancing costs as reported by Hirth et al., respectively. The evidence of grid-related costs is scattered and seems to depend crucially on geography. The most important finding of the literature review is that integration costs can become very high. When wind penetration reaches 30%–40%, integration costs can be in the range of 25–40 €/MWh at an average electricity price of approximately 70 €/MWh. This contrasts starkly with studies that, reviewing a subset of the effects we include here, report that “the hidden costs” of wind generation are “trivial” (Simshauser 2011).

Four additional findings can be identified in the literature: (i) integration costs increase with penetration; (ii) under most conditions, profile costs are higher than balancing costs even though the latter attracts more attention; (iii) integration costs increase significantly if the capital stock is not allowed to adapt. (The most important adaptation may be a shift in the thermal capacity mix from base-load to peak-load technologies); (iv) hydro reservoirs provide a large source of flexibility, making integration costs lower in hydro systems than in thermal systems.

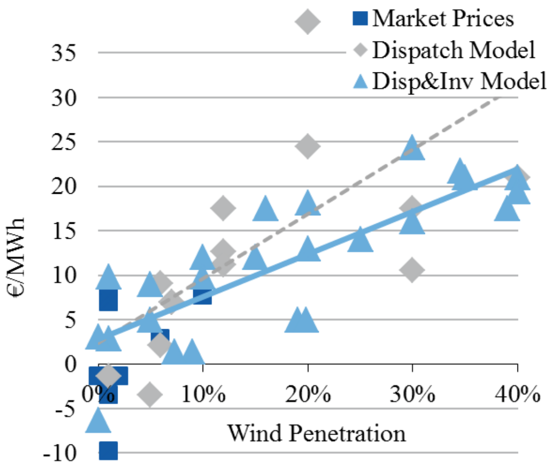

Figure 12: Wind profile cost estimates for thermal power systems from about 30 published studies. Studies are differentiated by how they determine electricity prices: from markets (squares), from short-term dispatch modeling (diamonds, dotted line), or from long-term dispatch and investment modeling (triangles, bold line). To improve comparability, the system base price has been normalized to 70 €/MWh in all the studies. Source and list of references: Hirth et al. (2013).

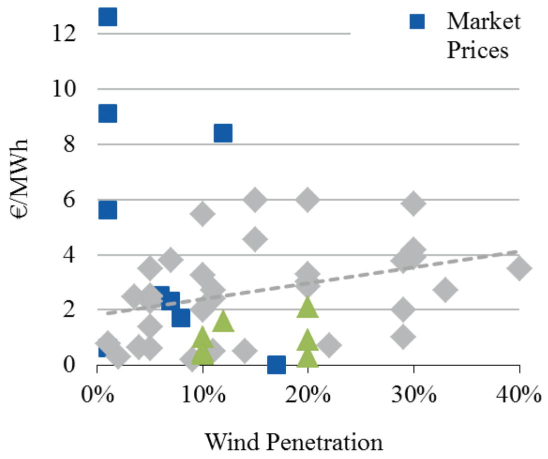

Figure 13: Wind balancing cost estimates for thermal power systems from about 20 published studies based on market prices (squares) or models (diamonds, dotted line). Three market-based studies report very high balancing costs, all other estimates are below 6 €/MWh. Studies of hydro-dominated systems show very low balancing costs (triangles). Source and list of references: Hirth et al. (2013).

High integration costs do not imply that optimal shares are low. Even IAMs that attach significant integration costs to wind often find high renewable shares under strict climate policy. Other studies use power market models to estimate optimal wind shares. Neuhoff et al. (2008) reports an optimal wind share for the UK of 40%. Hirth (2014) finds an optimal wind share of 20% [1-45%], roughly in line with Lamont (2008). Müsgens (2013) and Eurelectric (2013) reports an optimal wind share in Europe of more than one third by 2050, plus a positive optimal share for solar power. See Hirth (2014) for a more comprehensive review of optimal deployment model results for different model classes.

8. *Concluding remarks*

Physics shapes the economics of electricity. The laws of electromagnetism constrain storage, transmission, and flexibility. These constraints turn electricity into a good that is a heterogeneous along three dimensions - time, space, and lead-time. Consequently, different generation technologies, such as wind and coal power, produce different economic goods and hence have a different marginal value. Welfare maximization that ignores heterogeneity results in biased estimates. Economic analysis of power systems can (and should!) be done - but requires careful analysis and appropriate tools that take multi-dimensional heterogeneity into account. This paper provides an analytical welfare-economic framework for an assessment of power generators that explicitly accounts for heterogeneity. The framework offers a rigorous interpretation of commonly used cost indicators such as LCOE and grid parity – and points out flaws in the way they are often used.

As these indicators, multi-sector models often do not account for heterogeneity, implicitly equating the marginal value of different goods, and deliver biased results. The framework of this paper suggests a number of remedies: cost-benefit assessments require comparing the marginal costs of a generator to its marginal value; technologies can be compared in terms of costs, if System LCOE is used as a metric; multi-sector models should parameterize heterogeneity and/or iterate with high-resolution models. Other indicators, including grid parity, capacity credit, and curtailment, are recommended not to be used for economic assessment.

The most important policy implication of this assessment might be that there is none. In principle, markets are well equipped to price heterogeneity, in which case it does not constitute an externality. Then the variability of wind and solar power does not cause any external effects, and there is no need for policy interventions.

Looking closer, a few implications can be identified. First, as a general rule, wholesale markets should reflect all physical constraints and hence all dimensions of heterogeneity. Specifically, those (European) markets that do not price transmission congestion should do so. Moreover, the balancing system should be more market-oriented, with prices that reflect marginal costs and benefits and actors being allowed to respond to price signals. More than in other markets, governments and regulators shape the design of electricity markets; hence they are the ones that need to act. Second, it is not only wholesale prices that should reflect heterogeneity, but also retail prices. Retail prices should mirror the price spreads between hours, between locations, and real-time deviations from day-ahead markets. Implementing such prices should taking into account associated transaction costs, of course. Third, policy instruments should consider heterogeneity. Specifically, renewable support schemes should not absorb price fluctuations and socialize variability costs. While feed-in-tariffs do that, feed-in premiums and green certificate schemes allow price signals to reach investors.

At a very fundamental level, this papers shows that wind and solar are not that different from other generators in the end. Electricity itself is (very) different from other economic goods, but it is indeed questionable if it is sensible to draw a line between 'variable' and 'dispatchable' generators. Each generation technology has specific characteristics, and all technologies are subject to variability costs. However, at high penetration, the marginal value of wind and solar is lower than the value of other generators. Hence, taking heterogeneity seriously is especially relevant when assessing VRE under high penetration rates.

There are many directions for further research. Two seem to be particular relevant: on the one hand, considering electricity's heterogeneity in IAMs. Explicit modeling of some aspects of heterogeneity, parameterizing other aspects, and/or soft-coupling with high-resolution models can be part of the solution. This paper has discussed the fundamental welfare-economic problem and developed a few ideas, but much conceptual and implementation work remains to be done. On the other hand, sectoral models could be extended towards a 'super model' that captures all three dimensions of heterogeneity, and is able to assess the interaction between different dimensions. We hope this paper has contributed to spread awareness that such modeling is needed and helpful.

References

Amelin, Mikael (2009): "Comparison of Capacity Credit Calculation Methods for Conventional Power Plants and Wind Power", *IEEE Transactions on Power Systems* 24(2), 685-691.

Baker, Erin, Meredith Fowlie Derek Lemoine & Stanley Reynolds (2013): "The Economics of Solar Electricity", *Annual Review of Resource Economics* 5.

Bessembinder, Hendrik & Michael Lemmon (2002): "Equilibrium Pricing and Optimal Hedging in Electricity Forward Markets", *The Journal of Finance* LVII(3), 1347-1382.

Bessiere, F. (1970): "The investment 85 model of Electricite de France", *Management Science* 17 (4), B-192–B-211.

Black & Veatch (2012): *Cost and Performance Data for Power Generation Technologies. Prepared for the National Renewable Energy Laboratory*.

Bode, Sven (2013): "Grenzkosten der Energiewende - Teil 1: Eine Neubewertung der Stromgestehungskosten von Windkraft- und Photovoltaikanlagen im Kontext der Energiewende", *Arrhenius Institute Discussion Paper* 8.

Boiteux, Marcel (1949): "Peak-Load Pricing", reprint (1960) *The Journal of Business* 33(2), 157 – 179.

Borenstein, Severin (2008): "The Market Value and Cost of Solar Photovoltaic Electricity Production", *CSEM Working Paper* 176.

Borenstein, Severin (2012): "The Private and Public Economics of Renewable Electricity Generation", *Journal of Economic Perspectives* 26(1), 67–92.

Breyer, Christian & Alexander Gerlach (2013): "Global overview on grid-parity", *Progress in photovoltaics* 21(1), 121-136.

BSW (2011): *Solarenergie wird wettbewerbsfähig*, Bundesverband Solarwirtschaft, www.solarwirtschaft.de/fileadmin/media/pdf/anzeige1_bsw_energiewende.pdf.

Clover, Robert (2013): "Energy Mix In Europe to 2050", *paper presented at the 2013 EWEA conference*, Vienna.

Covarrubias, A (1979): "Expansion Planning for Electric Power Systems", *IAEA Bulleting* 21(2/3), 55-64.

Crew, Michael, Chitru Fernando & Paul Kleindorfer (1995): "The Theory of Peak-Load Pricing. A Survey", *Journal of Regulatory Economics* 8, 215 – 248.

Edenhofer, Ottmar, Lion Hirth, Brigitte Knopf, Michael Pahle, Steffen Schloemer, Eva Schmid & Falko Ueckerdt (2013): "On the Economics of Renewable Energy Sources", *Energy Economics* (forthcoming).

EIA (2013): *Annual Energy Outlook 2013*, U.S. Energy Information Administration.

Ensslin, Cornel, Milligan, Michael, Holttinen, Hannele, O'Malley, Mark and Keane, Andrew (2008): "Current methods to calculate capacity credit of wind power, IEA collaboration", *Proceedings of the Power and Energy Society General Meeting*, Pittsburgh.

EPIA (2011): *Solar Photovoltaics competing in the energy sector*, European Photovoltaic Industry Association, www.epia.org/news/publications/

Eurelectric (2013). *PowerChoices Reloaded*, Brussels (forthcoming).

Fischedick, M, R Schaeffer, A Adedoyin, M Akai, T Bruckner, L Clarke, V Krey, I Savolainen, S Teske, D Ürge-Vorsatz & R Wright (2011): „Mitigation Potential and Costs", in: O Edenhofer, R Pichs-Madruga, Y Sokona, K Seyboth, P Matschoss, S Kadner, T Zwickel, P Eickemeier, G Hansen, S Schlömer and C v Stechow (Eds.): *IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation*, Cambridge University Press, Cambridge, UK.

Fraunhofer ISE (2013): *Photovoltaics report*, Fraunhofer Institute for Solar Energy Systems, www.ise.fraunhofer.de/mwg-internal/de5fs23hu73ds/progress?id=94T8LFoGsA&dl.

Fripp, Matthias & Ryan H. Wiser (2008): "Effects of Temporal Wind Patterns in the value of wind-generated Electricity in California and the Northwest", *IEEE Transactions on Power Systems* 23(2), 477 – 485.

GE Energy (2010): "Western Wind and Solar Integration Study", *NREL Subcontract Report* SR-550-47434.

GEA (2012): *Global Energy Assessment - Toward a Sustainable Future*, Cambridge University Press, Cambridge, UK.

Gowrisankaran, Gautam, Stanley S. Reynolds & Mario Samano (2011): "Intermittency and the Value of Renewable Energy", *NBER Working Paper* 17086

Green, Richard (2005): "Electricity and Markets," *Oxford Review of Economic Policy* 21(1), 67–87.

Gross, Robert, Philip Heptonstall, Dennis Anderson, Tim Green, Matthew Leach & Jim Skea (2006): *The Costs and Impacts of Intermittency: An assessment of the evidence on the costs and impacts of intermittent generation on the British electricity network*, www.uwig.org/mwg-internal/de5fs23hu73ds/progress?id=GxdIkw+r0n.

Grubb, Michael (1991): "Value of variable sources on power systems", *IEE Proceedings of Generation, Transmission, and Distribution* 138(2) 149-165.

Heide, Dominik, Lueder von Bremen, Martin Greiner, Clemens Hoffmann, Markus Speckmann & Stefan Bofinger (2010): "Seasonal optimal mix of wind and solar power in a future, highly renewable Europe", *Renewable Energy* 35, 2483-2489.

Hirth, Lion (2013a): "The Market Value of Variable Renewables", *Energy Economics* 38, 218-236.

Hirth, Lion (2014): "The Optimal Share of Variable Renewables", *The Energy Journal* 36(1), 127-162.

Hirth, Lion (2014b): "The market value of solar photovoltaics: Is solar power cost-competitive?", *IET Renewable Power Generation* (submitted).Hirth, Lion, Falko Ueckerdt & Ottmar Edenhofer (2013): "Integration Costs and the Value of Wind Power. Thoughts on a valuation framework for variable renewable electricity sources", *USAEE Working Paper* 13-149.

Hirth, Lion & Falko Ueckerdt (2013a): "Redistribution Effects of Energy and Climate Policy", *Energy Policy* 62, 934-947.

Hirth, Lion & Falko Ueckerdt (2013b): "The Decreasing Market Value of Variable Renewables: Integration Options and Deadlocks", in: Deltlef Stolten & V Scherer (eds.): *Transition to Renewable Energy Systems*, Wiley.

Hirth, Lion, Falko Ueckerdt & Ottmar Edenhofer (2013): "Integration Costs and the Value of Wind Power. Thoughts on a valuation framework for variable renewable electricity sources", *USAEE Working Paper* 13-149.

Hirth, Lion & Inka Ziegenhagen (2013a): "Balancing power and variable renewables", *USAEE Working Paper* 13-154.

Holttinen, Hannele & Göran Koreneff (2012): "Imbalance costs of wind power for a hydropower producer in Finland", *Wind Engineering* 36(1), 53-68.

Holttinen, Hannele (2005): "Optimal electricity market for wind power", *Energy Policy* 33(16), 2052-63.

Holttinen, Hannele, Peter Meibom, Antje Orths, Bernhard Lange, Mark O'Malley, John Olav Tande, Ana Estanqueiro, Emilio Gomez, Lennart Söder, Goran Strbac, J Charles Smith, Frans van Hulle (2011): "Impacts of large amounts of wind power on design and operation of power systems", *Wind Energy* 14(2), 179 – 192.

IEA (2011): *Harnessing Intermittent Renewables*, International Energy Agency, Paris.

IEA (2012): *World Energy Outlook 2012*, International Energy Agency, Paris.

IEA (2013): *Renewable Energy Mid-Term Market Outlook*, International Energy Agency, Paris.

IEA (2014): *The Power of Transformation – Wind, Sun and the Economics of Flexible Power Systems*", International Energy Agency, Paris.

IEA & NEA (2011): *Projected costs of generating electricity*, International Energy Agency and Nuclear Energy Agency, Paris.

IRENA (2012): *Renewable Power Generation Costs in 2012: An Overview*, International Renewable Energy Agency.

Jenkins, R & D Joy (1974): "Wien Automatic System Planning Package (WASP) - An Electric Utility Optimal Generation Expansion Planning Computer Code", *USAEC Report* ORNL-4945.

Johansen, Leif (1960): *A Multi-Sectoral Study of Economic Growth*, North-Holland.

Joskow, Paul (2011): "Comparing the Costs of intermittent and dispatchable electricity generation technologies", *American Economic Review Papers and Proceedings* 100(3), 238–241.

Karlynn, Cory and Schwabe, Paul (2009): "Wind Levelized Cost of Energy: A Comparison of Technical and Financing Input Variables", *NREL Technical Report* TP-6A2-46671.

Keane, Andrew, Milligan, Michael, Dent, Chris, Hasche, Bernhard, D'Annunzio, Claudine, Dragoon, Ken, Holttinen, Hannele, Samaan, Nader, Soder, Lennart, and O'Malley, Mark (2011): "Capacity Value of Wind Power" *IEEE Transactions on Power Systems* 26(2), 564–572.

Knopf, Brigitte, Bjorn Bakken, Samuel Carrara, Amit Kanudia, Ilkka Keppo, Tiina Koljonen, Silvana Mima, Eva Schmid & Detlef van Vuuren (2013): "Transforming the European energy system: Member States' prospects within the EU framework. Paper of the EMF28 model comparison of the EU Energy Roadmap", *Climate Change Economics.*

Koch, Oliver (2013): "Capacity mechanisms", *Paper presented at the 13th European IAEE Conference,* Düsseldorf.

Kost, Christoph, Thomas Schlegl, Jessica Thomsen, Sebastian Nold & Johannes Mayer (2012): *Stromgestehungskosten Erneuerbarer Energien*, Fraunhofer ISE, www.ise.fraunhofer.de/de/presse-und-medien/presseinformationen/presseinformationen-2012/erneuerbare-energietechnologien-im-vergleich

Lamont, Alan (2008): "Assessing the Long-Term System Value of Intermittent Electric Generation Technologies", *Energy Economics* 30(3), 1208-1231.

Lamont, Alan (2012): "Assessing the Economic Value and Optimal Structure of Large-scale Energy Storage", *IEEE Transaction on Power Sytems* 28(2), 911-921.

Leontief, Wassily (1941): *The Structure of American Economy, 1919–1929*, Harvard University Press, Cambridge.

Luderer, Gunnar, et al. (2013): "The role of renewable energy in climate stabilization: results from the EMF27 scenarios", *Climate Change* (forthcoming).

Madaeni, Seyed Hossein, Sioshansi, Ramteen, and Denholm, Paul (2012): "Comparing capacity value estimation techniques for photovoltaic solar power", *IEEE Journal of Photovoltaics* 3(1).

Martin, Brian & Mark Diesendorf (1983): "The economics of large-scale wind power in the UK: a model of an optimally mixed CEGB electricity grid", *Energy Policy* 11(3), 259 – 266.

Milligan, Michael, Erika Ela, Bri-Mathias Hodge, Brendan Kirby, Debra Lew, Charlton Clark, Jennifer DeCesaro & Kevin Lynn (2011): "Integration of Variable Generation, Cost-Causation, and Integration Costs", *Electricity Journal* 24(9), 51 – 63, also published as *NREL Technical Report* TP-5500-51860.

Milligan, Michael, Hannele Holttinen, Brendan Kirby, Juha Kiviluoma, Ana Estanqueiro, Sergio Martín-Martínez, Emilio Gómez-Lázaro, Iván Pineda & Charlie Smith (2013): "Wind integration cost and cost-causation", *Proceedings of the 12th Wind Integration Workshop*, London.

Möst, Dominik & Wolf Fichtner (2010): "Renewable energy sources in European energy supply and interactions with emission trading", *Energy Policy* 38, 2898 – 2910.

Müsgens, Felix (2013): "Equilibrium Prices and Investment in Electricity Systems with CO2-Emission Trading and High Shares of Renewable Energies", *paper presented at the Mannheim Energy Conference* 2013.

Nagl, Stephan, Michaela Fürsch & Dietmar Lindenberger (2012): „The costs of electricity systems with a high share of fluctuating renewables - a stochastic investment and dispatch optimization model for Europe", *EWI Working Paper* 01/2012.

Nagl, Stephan, Michaela Fürsch, Cosima Jägermann & Marc Oliver Bettzüge (2011): "The economic value of storage in renewable power systems - the case of thermal energy storage in concentrating solar plants", *EWI Working Paper* 08/2011.

NEA (2012): *Nuclear Energy and Renewables - System Effects in Low-carbon Electricity Systems*, Nuclear Energy Agency, Paris.

NEA (2012): *Nuclear Energy and Renewables - System Effects in Low-carbon Electricity Systems*, Nuclear Energy Agency, Paris.

Neuhoff , Karsten, Andreas Ehrenmann, Lucy Butler, Jim Cust, Harriet Hoexter, Kim Keats, Adam Kreczko & Graham Sinden (2008): "Space and time: Wind in an investment planning model", *Energy Economics* 30, 1990 – 2008.

Nicolosi, Marco (2012): *The Economics of Renewable Electricity Market Integration. An Empirical and Model-Based Analysis of Regulatory Frameworks and their Impacts on the Power Market*, Ph.D. thesis, University of Cologne.

Nitsch, Joachim, Thomas Pregger, Yvonne Scholz, Tobias Naegler, Michael Sterner, Norman Gerhardt, Amany von Oehsen, Carsten Pape, Yves-Marie Saint-Drenan & Bernd Wenzel (2010): *Langfristszenarien und Strategien für den Ausbau der erneuerbaren Energien in Deutschland bei Berücksichtigung der Entwicklung in Europa und global (Leitstudie 2010)*, www.bmu.de/files/pdfs/allgemein/application/pdf/leitstudie2010_bf.pdf

Obersteiner, Carlo, T Siewierski, A N Andersen (2010): "Drivers of imbalance cost of wind power: a comparative analysis", *Proceedings of the 7th European Energy Markets Conference*, Madrid.

Perez, Richard, Mike Taylor, Tom Hoff & J P Ross (2008): "Reaching Consensus in the Definition of Photovoltaics Capacity Credit in the USA: A Practical Application of Satellite-Derived Solar Resource Data," IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 1(1), 28–33.

Phillips, D Jenkin, J Pritchard & K Rybicki (1969): "A Mathematical Model for Determining Generating Plant Mix", *Proceedings of the Third IEEE PSCC*, Rome.

Pinson, Pierre, Christophe Chevallier & George Kariniotikas (2007) : "Trading Wind Generation From Short-Term Probabilistic Forecasts of Wind Power", *IEEE Transactions on Power Systems* 22(3), 1148-56.

REN21 (2013): *Renewables 2013 Global Status Report*, REN21 Secretariat, Paris.

Schröder, Andreas, Friedrich Kunz, Jan Meiss, Roman Mendelevitch & Christian von Hirschhausen (2013): "Current and Prospective Production Costs of Electricity Generation until 2050", *DIW Data Documentation* 68.

Smith, Charles, Michael Milligan, Edgar DeMeo & and Brian Parsons (2007): "Utility Wind Integration and Operating Impact State of the Art", *IEEE Transactions on Power Systems* 22(3), 900 – 908.

Sims, R., P. Mercado, W. Krewitt, G. Bhuyan, D. Flynn, H. Holttinen, G. Jannuzzi, S. Khennas, Y. Liu, M. O'Malley, L. J. Nilsson, J. Ogden, K. Ogimoto, H. Outhred, Ø. Ulleberg & F. v. Hulle (2011): "Integration of Renewable Energy into Present and Future Energy Systems". In: *IPCC Special Report on Renewable Energy Sources and Climate*. O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer and C. v. Stechow, Eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Simshauser, Paul (2011): "The Hidden Costs of Wind Generation in a Thermal Power System: What Cost?", *Australian Economic Review* 44(3), 269-292.

Stoughton, M, R Chen & S Lee (1980): "Direct construction of the optimal generation mix", *IEEE Transactions on Power Apparatus and Systems* 99(2), 753-759.

Sullivan, P., V. Krey & K. Riahi (2013): "Impacts of Considering Electric Sector Variability and Reliability in the MESSAGE Model," *Energy Strategy Reviews* 1(3), 157-163.

Swider, Derk & Christoph Weber (2006): "An Electricity Market Model to Estimate the Marginal Value of Wind in an Adapting System", *Proceedings of the Power Engineering Society General Meeting*, Montreal.

Taylor, L & S Black (1974): "Practical General Equilibrium Estimation of Resources Pulls under Trade Liberalization", *Journal of International Economics* 4(1), 37-58.

Ueckerdt, Falko, Lion Hirth, Gunnar Luderer & Ottmar Edenhofer (2013a): "System LCOE: What are the costs of variable renewables?", *Energy* (forthcoming).

Ueckerdt, Falko, Lion Hirth, Simon Müller & Marco Nicolosi (2013b): "Integration costs and Marginal value. Connecting two perspectives on evaluating variable renewables", *Proceedings of the 12th Wind Integration Workshop*, London.

VGB PowerTech (2011): *Investment and Operation Cost Figures – Generation Portfolio*, VGB PowerTech e.V., Essen

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