Optimal Electricity Generation Portfolios in the Presence of Fuel Price and Availability Risks

by

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Abstract

This paper addresses the question of how an optimal electricity generating portfolio comprising both fossil and renewable technologies should look like if the decision maker wishes to minimize not the classical overall Levelized Costs Of Electricity (LCOE), but the risk-adjusted ones in the framework of Markowitz´ Modern Portfolio Theory (MPT), subject to load-satisfying constraints. Thereby the well-established relation of monotonically increasing system costs for increasing Renewable Energy Sources (RES) - shares is considered in the optimization, which represents the first contribution to the scientific literature.

While most of the scientific literature on MPT with application to electricity generating technologies focusses on only one source of uncertainty, be it in the form of price or availability risk, the current work takes both risk types simultaneously into account in the optimization, thus guaranteeing a fair(er) assessment of thermal and renewable technologies. This addition constitutes the second contribution to the scientific literature. This paper contains a new model for determining optimal electricity generating technologies, an analytic solution to it and an application of the model via a parametrization for Germany as a case study.

1. Introduction

The in Germany originated term of "energy revolution" is currently being addressed more often than ever even outside the German borders, posing the biggest challenge of the 21st century not only to Germany and Europe but to the entire world. A gradual insertion of renewable energy sources (RES) is planned as a transition process towards a secure, sustainable and environmentally friendly electricity generation. First steps in this process have already been implemented leading to first effects that have already been induced such as increased frequency and duration of negative electricity prices, additional system costs, falling CO_2 emissions etc.

At European level, substantial governmental and supranational interventions in the composition of the national electricity generating portfolios have been either announced or partially already implemented. Worthy of mentioning in this context are *restrictive measures* on the one side and *supporting ones* on the other side.

Maybe one of the most important examples of a restrictive measure is the Fukushima-induced exit from nuclear power already announced by several leading European countries starting with Germany, which stated that by 2020 all nuclear reactors will be shut down. Italy, Belgium and Switzerland followed and even France, which is the European leader in nuclear power, promised through its now former president Francois Hollande a reduction of the nuclear power share from 75% to about 50% of the overall electricity generating portfolio.

On the other hand, one can clearly observe supportive interventions such as subsidies for several technologies, especially for renewable ones like wind, solar PV, biomass but also for so-called mixed technologies like Combined Heat and Power (CHP) plants.

Another aspect motivating the consideration of optimal electricity generating portfolios is the increasing ecological importance evoked by the now highly mediatized climate change. The latter is supposedly caused by anthropologically induced CO_2 emissions brought about by fossil fuels. One way to steer in the direction of a cleaner electricity production is through the 2005 established market for so-called European Emission Allowances (EUAs), which puts lot of pressure on dirty fossil fuels.

A third phenomenon that can currently be observed is the worldwide forecasted growing electricity demand, which is strongly connected with another widely thematised phenomenon i.e. urbanisation. Demand for electricity is expected to increase most of all in Asia, with China and India developing at the highest paces.

In the given context, it is therefore necessary to ask the question of a revision for economically optimal electricity generating portfolios, from both a social planner´s perspective but also a private investor´s one.

This paper focuses on economical decision-making criteria from a social planner´s perspective. The decision-maker can select from several technologies, whereby a rough classification in thermal and renewable technologies is being made, where wind is representatively taken for the renewable technology. Both types of technologies pose advantages and disadvantages: thermal technologies are dispatchable but dirty and dependent on volatile fuel prices, whereas the renewable ones are clean but not-dispatchable, but showing off availability variations and therefore higher system costs. This paper elaborates on how a cost-optimal electricity generating portfolio looks like if two defining types of volatility are being considered: fuel price and wind availability volatilities, whereby the latter is associated with higher system costs.

2. Methods

2.1. Introduction: Modern Portfolio Theory (MPT)

Portfolio optimization represents the selection process of shares of different assets in a portfolio such that this portfolio is better than any other according to a certain criterion.

Modern Portfolio Theory (MPT) came to life in 1952 thanks to Markowitz´s paper Nobel-prize winning paper entitled “Portfolio Selection” and originally stems from the field of finance. It is based on the general assumption of risk aversion for investors and uses returns as input data for the model. MPT is characterized by an existing trade-off between profit (measured by the classical expectation) and risk (measured via the variance). One of the most important effects associated to this theory is the diversification of different assets as a protection mechanism against losses.

The main results uncovered by MPT are existence and uniqueness of a solution for exactly one combination maximizes the portfolio return for each level of risk. Furthermore, one can obtain the set of all optimal combinations that results when one assumes that not all investors have the same level of risk aversion, but the latter is varied. The set of all these optimal combinations is called *efficient frontier*.

2.2. Introduction: MPT in Electricity Economics

The two biggest differences between the classical MPT with application in finance and MPT applied to electricity economics are first, that investments in financial assets are obviously not possible any more, but in real assets, and second, that returns are no longer used as input data, but several other possibilities exist, which developed in independent research streams on their own: levelized costs of electricity (EUR/MWh),

capacity factors (kWh/MW), net present value (EUR) and internal rate of return (%). This paper mostly focuses on the levelized costs of electricity-stream with the additional inclusion not of capacity, but of availability factors for wind.

From a mathematical point of view, the difference to finance is more pronounced and goes beyond the adoption of distinct input data. One of the fundamental differences is without a doubt the brutal restriction of the decision variable to be positive for no negative generation can exist in electricity economics, whereas in finance short-selling is allowed, making this restriction obsolete. The biggest difference, however, resides in the fact that in electricity economics the problem is a minimization of costs, whereas in finance the decision maker maximizes his or her profits less the costs associated with the measure of risk assumed in and used throughout the model.

2.3. Analytical Model

2.3.1. Cost Components

As previously specified, this paper makes a rough classification of the electricity generating technologies in thermal and renewable, whereas for the latter a special focus on wind is laid. Therefore the cost structure considered in this paper is also classified accordingly, as can be seen in Table 1.

Cost Type	Thermal	Renewable
Investment Costs	✓	✓
Fixed O&M Costs	✓	✓
Variable O&M Costs	✓	✓
Fuel Costs	✓	×
Additional System Costs	×	✓

Table 1: Cost Components Considered in the Optimization Model *(Source: own illustration)*

For both technology types, investment costs, fixed as well as operation and maintenance costs are included in the modelling, however the differentiation between the two of them occurs when looking at the last two components. Consequently, fuel costs are only considered for the thermal technologies since renewable technologies do not exhibit such costs per definition but cause additional system costs instead, which cannot be accounted for by thermal technologies.

2.3.2. Additional System Costs

When addressing the topic of additional system costs, the specialized literature teaches us that they can be split into two parts: *balancing* and *reliability costs*.

Balancing costs are short-term operational costs that arise because of the variability and uncertainty of the produced output i.e. electricity in this case. These costs are therefore associated with forecast errors on the one hand and with the availability variation that is typical for renewable energy sources.

Reliability costs are costs that arise because of the additional capacity needed to ensure system reliability at any time. Theoretically, it is possible that wind just simply does not blow. In this case, even the portion of demand generally satisfied by wind needs to be covered, which is why reserve (thermal) capacity is necessary.

Linear and non-linear OLS estimations based on data on wind integration are shown in Figure 1, where it can be seen that the quadratic estimation without intercept appears to be the poorest fit because of the downward part for wind generation shares above 30% since the balancing costs should sky-rocket for higher

wind generation shares. For this paper, the linear estimation without intercept is relevant and will be used further on. An identical analysis has also been performed for reliability costs as well.

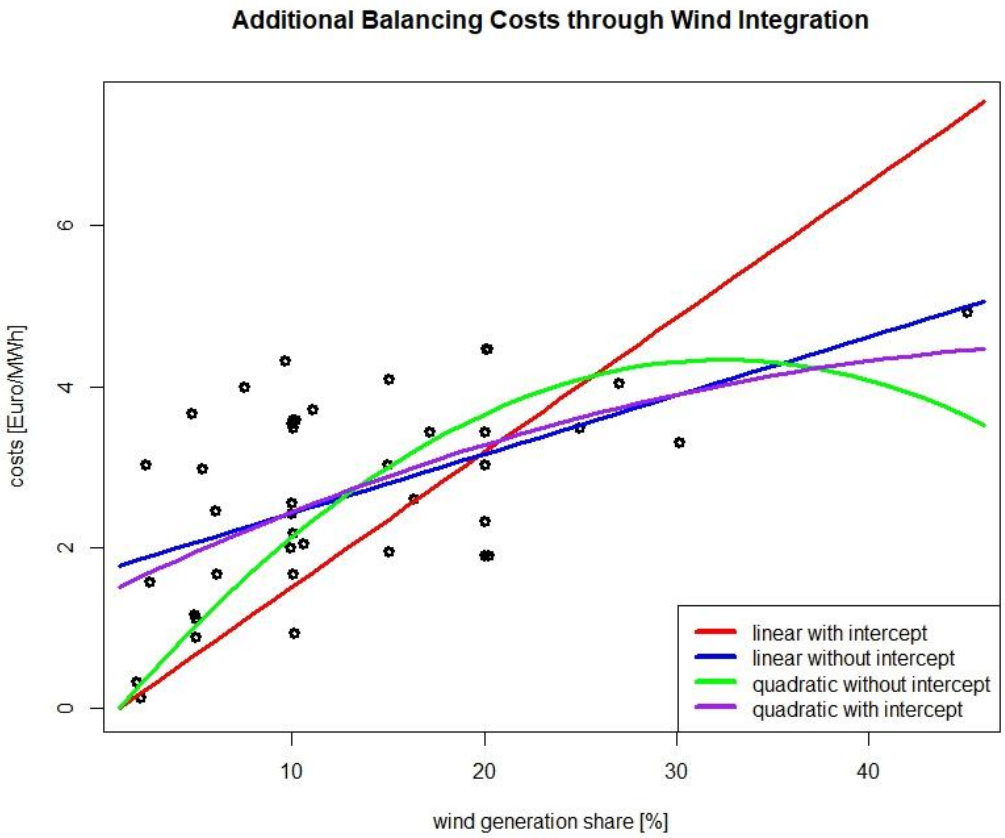

Figure 1: Linear and Quadratic Estimations for Balancing Costs *(Source: own illustration)*

2.3.3. Optimal Discretisation of the Load Duration Curve (LDC)

Any portfolio model for electricity generation would be superfluous without a proper consideration of the load, which, mathematically speaking, constitutes a huge restriction. A very elegant way to account for the load for the entire 8760 of a normal year is via the Load Duration Curve (LDC), which orders all load levels observed throughout one year in decreasing order of their duration.

What we are generally interested in, is not the load level per se shown by the LDC, but the area under the curve i.e. the generation corresponding a certain capacity level, which implies the need for the inverse function of the continuous estimation of the LDC and its integral.

Because of the complexity of this problem and of the (still) limited calculating capabilities of modern PCs, a discretization of the LDC in several load blocks is necessary to include the demand restrictions, but somehow ensure solvability.

For the discretization of the LDC, an optimization model was used to determine the optimal load factors corresponding the blocks such that the error between the summed area of the blocks and the area under the curve is minimized.

Mathematically speaking, this can be formulated as an optimization problem as seen below, where LF stands for the normalized load factor, restricted to the interval [0,1], and D(LF) represents the normalized version of the (continuous) parametric estimation of the LDC

$$\min_{\mathsf{LF}_n} \quad \sum_{n=1}^{N} (\mathsf{LF}_n - \mathsf{LF}_{n-1}) D(\mathsf{LF}_{n-1}) - \int_{\mathsf{LF}_{n-1}}^{\mathsf{LF}_n} D(l)\mathrm{d}l$$

$$\text{s.t.} \int_{\mathsf{LF}_{n-1}}^{\mathsf{LF}_n} D(l)\mathrm{d}l \approx \sum_{n=1}^{N} (\mathsf{LF}_n - \mathsf{LF}_{n-1}) \frac{D(\mathsf{LF}_{n-1}) + D(\mathsf{LF}_n)}{2}$$

$$\mathsf{LF}_0 = 0 \leq \mathsf{LF}_n \leq 1 = \mathsf{LF}_N, \quad D'(l) \leq 0.$$

It is trivial to prove that the more blocks one has, the smaller the error. Since, for computational reasons, only a limited number of blocks can be considered, one needs to restrict oneself to a small number of load blocks. In the course of the paper, the restriction has been imposed to three load blocks, however, below, in Figure 2, the optimal discretisation of the LDC for eight load blocks is shown for illustrative purposes.

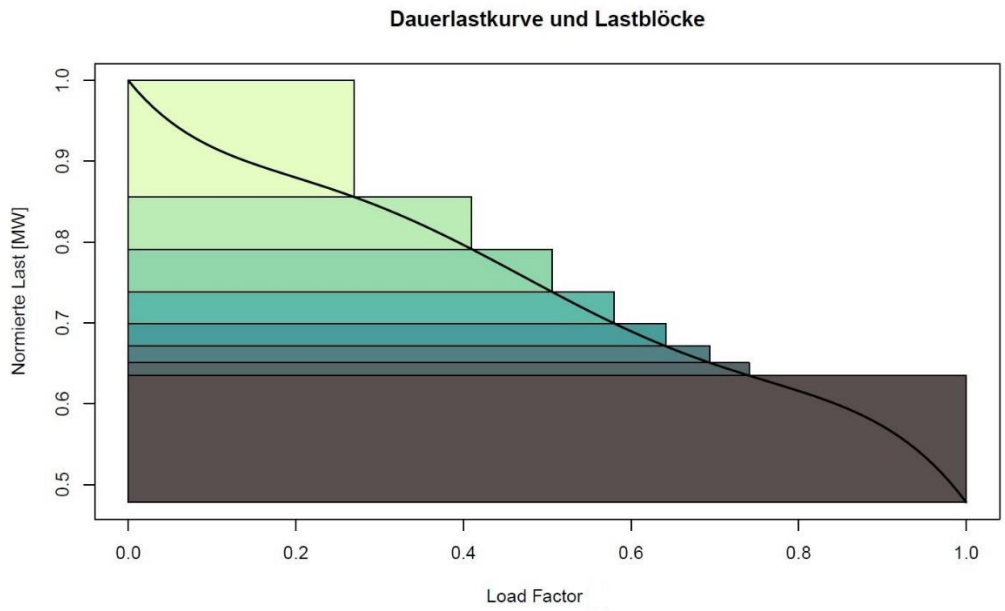

Figure 2: Optimal Discretisation of the LDC via Eight Load Blocks *(Source: own illustration)*

2.3.4. Overall Model

Let *I* be the number of load blocks used to discretely approximate the LDC and *J* be the number of technologies considered, with *J-1* thermal technologies and the Jth technology being the renewable one, namely wind.

In accordance with MPT applied to electricity economics, the objective function is to minimize the risk-adjusted LCOE, with *β* being a parameter reflecting the decision-maker's risk aversion and x_{ij} the decision variable representing electricity generation in block *i* with technology *j*.

$$\min_{x_{ij}, i \in I, j \in J} \quad \mathbb{E}[c^{LCOE}] + \frac{\beta}{2} \mathbb{V}ar[c^{LCOE}]$$

$$\text{s.t.} \quad \underbrace{\begin{pmatrix} x_{11} & \dots & x_{1J} \\ \vdots & \ddots & \vdots \\ x_{I1} & \dots & x_{IJ} \end{pmatrix}}_{X} \begin{pmatrix} 1 \\ \vdots \\ \mathbb{E}[A] \end{pmatrix} = \begin{pmatrix} D_1 \\ \vdots \\ D_I \end{pmatrix}$$

$$X \geq 0$$

By contrast with the scientific literature, this paper's LCOE also include the system costs as a linear function of the decision variable, meaning from a mathematical point of view that the objective function is no longer a quadratic, but a fourth degree polynomial. Also, for each thermal technology, the fuel cost component of the LCOE is modelled as a stochastic variable.

The optimally determined load blocks come into play as part of the first constraint matrix, more specifically on the right hand side, the vector $(D_1,\ldots,D_l)^T$ resulting as the easily computable area of each optimally determined load block. *A* is a stochastic variable standing for the [0,1]-restricted availability factor for wind.

The second matrix constraint is a non-negativity constraint introduced to mathematically model what in reality cannot happen: that electricity generation becomes negative.

2.3.5. Solution

As a static, non-linear but convex optimization problem (which guarantees existence and uniqueness of a solution), an analytical solution to the above model is obtained by applying the *Karush-Kuhn-Tucker theorem*. Ultimately, obtaining the optimal solution reduces to finding the roots of a system of equations derived from the model's gradients. For this, the Newton-Raphson method is applied.

2.4. Parametrisation

The above overall model is implemented for 3 load blocks, representing *base, intermediate and peak load*, respectively, and 4 technologies: 3 thermal (*gas, coal and nuclear*) and 1 renewable (*wind*).

Data for each technology for investment costs, fixed and variable operations and maintenance costs was taken from the specialized literature, with special emphasis on Germany. The 2 types of stochastic variables (wind availability and fuel price) are fed historical monthly data from the time frame 1990-2016. Since all 3 thermal technologies exhibit the same type of stochastic variable (fuel cost), but different fuel inputs (gas, coal and uranium), an analysis of the historical correlations between all combinations of the 3 of them is necessary.

Figure 3 illustratively displays a 2-dimensional density plot displaying the correlation between 2 of the most likely correlated random variables i.e. coal and gas. A high degree of correlation can be easily observed between the two of them.

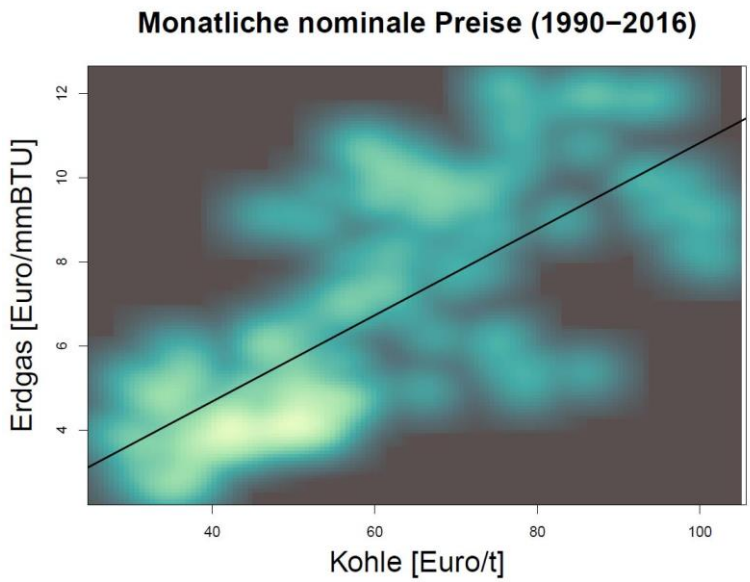

Figure 3: 2-Dimensional Density Plot of Coal and Gas *(Source: own illustration)*

On the other hand, an analysis of the second type of stochastic variable was undertaken, whereby data on varying wind speeds were used for one illustratively taken location: Brocken (Northern Germany). By considering the technical features of a wind turbine, such as the cut-in, rated and cut-out wind speeds, availabilities factors in the interval [0,1] can be found. The yearly mean of the latter was computed and the density of the resulting yearly availability factor plotted, see Figure 4.

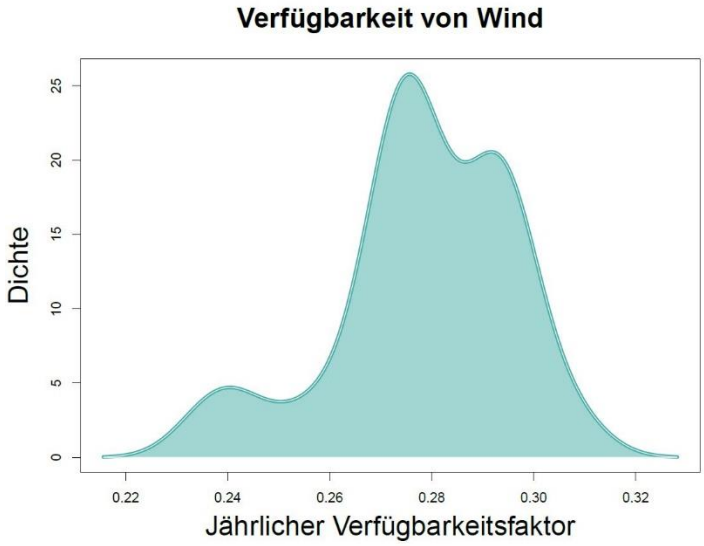

Figure 4: Density of the Yearly Availability Factor for Wind in Brocken *(Source: own illustration)*

3. Results

The model was run with and without the consideration of system costs to isolate the difference this cost component actually makes.

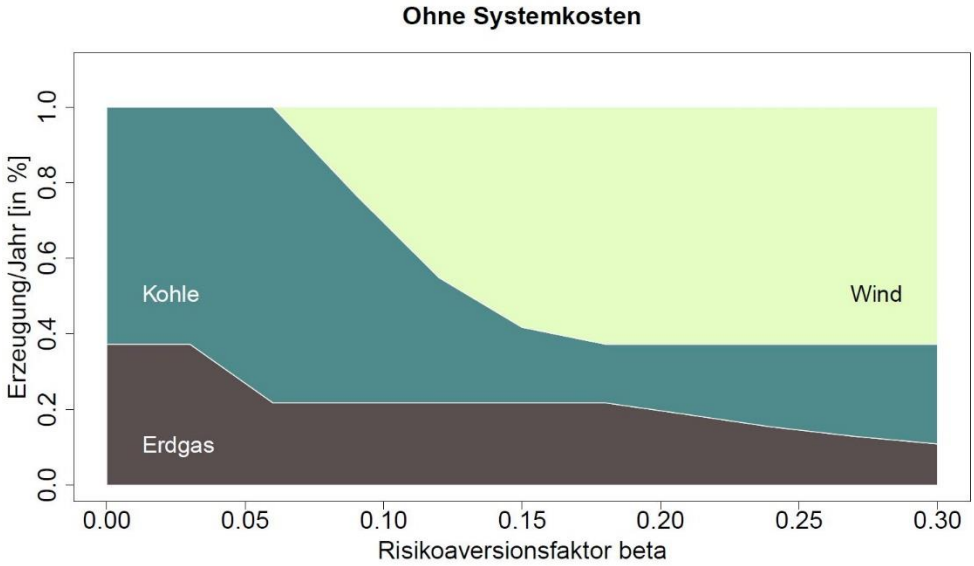

Figure 5: Optimal Portfolio Shares on the Efficient Frontier for the Case "Without System Costs" *(Source: own illustration)*

First, when excluding system costs, one can observe in Figure 5 that because of its relatively low capacity factor and because of the high volatility of its fuel costs, gas is only used for peak load satisfaction for high

risk aversions. Coal, on the other hand has a lower volatility of fuel costs, however for high risk aversions, it is successively replace by wind. Nuclear power plants are not part of the optimal portfolio.

As can be seen below in Figure 6, if system costs are indeed included, wind is still part of the optimal portfolio for high risk aversions, though to a considerably smaller extent. Nuclear power plants are present as an additional diversification instrument against the fuel price risks of coal and gas, for relatively high risk aversion parameters.

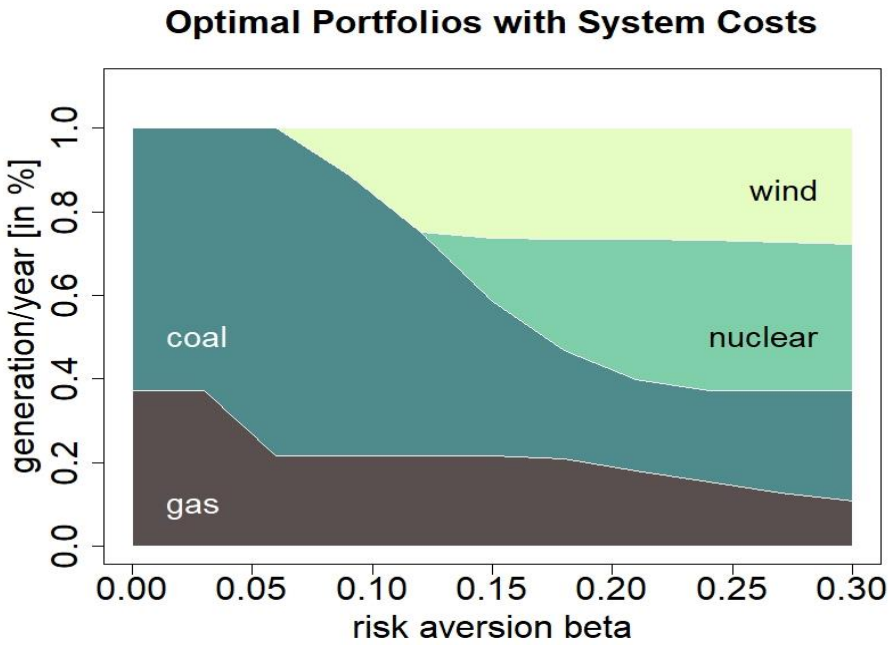

Figure 6: Optimal Portfolio Shares on the Efficient Frontier for the Case "With System Costs"
(Source: own illustration)

4. Conclusion

If the decision maker does not consider system costs, the diversification effect of wind is greatly over-estimated. Should system costs be considered, the diversification effect of wind persists, however to a smaller extent.

A simultaneous consideration of both risk factors (fuel price and availability) seems indispensable.

From a mathematical perspective, adding system costs leads to a non-linear, non-quadratic problem, which suffers from the curse of dimensionality. This means that a trade-off exists between *precision* (given by as many load blocks and technologies as possible) and *solvability*.

5. References