Efficient Multi-Energy Generation Portfolios for the Future

by

Florian Kienzle and Göran Andersson

Contact information:
Florian Kienzle, Dipl.-Ing. Energy Engineering
ETH Zurich, Power Systems Laboratory
Physikstrasse 3, 8092 Zurich, Switzerland
Phone: +41 44 632 89 25 / Email: kienzle@eeh.ee.ethz.ch

Abstract

This paper introduces the application of mean-variance portfolio theory to portfolios generating multiple forms of energy such as electricity, heating or cooling power. Portfolio theory has already been successfully applied to several cases of electricity generation planning. A general extension of this method to an arbitrary number of output energies will be developed in this paper. Instead of calculating means and variances from time series of historical data - as it is commonly done - a set of several possible scenarios is used. By this means, the model allows to appropriately take into account uncertainties about future developments, which may be able to alter the economic performance of the considered generation technologies. In order to illustrate the proposed method, the model is applied to a portfolio of distributed electricity and heat generation technologies. In so doing, it is shown how efficient risk-return combinations for multi-energy generation portfolios can be determined.

1 Introduction

Optimally designed energy infrastructures should be able to satisfy all types of energy demand in an environmentally sustainable, secure and competitive way. Of course, actual solutions will always have to be a trade-off and it will never be possible in reality to completely bring into line these three criteria. During the last years, however, the planning of energy systems has been further complicated by several factors, which make it even more difficult to find the best possible trade-off between relevant planning criteria.

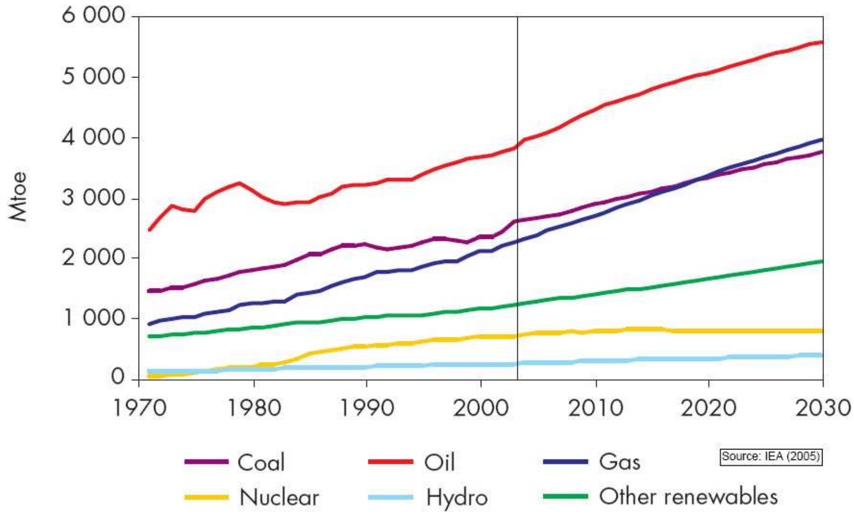

Figure 1: World primary energy demand by fuel in the past and projections for the future based on the reference scenario in the IEA World Energy Outlook 2005.

First of all, mankind's thirst for energy seems to be quenchless. The worldwide demand for primary energy has been increasing over the last decades and, as Fig. 1 shows, according to the reference scenario of the IEA in [1] it will continue to grow. Regarding the supply side, the IEA predicts the peak of non-OPEC conventional crude oil output by the middle of the next decade [2]. When the increase in demand is accompanied by a decrease in supply, prices of primary energy sources will unavoidably rise. High prices, however, represent a threat to the global economy and can undermine geopolitical stability in the worst case.

Another factor affecting the planning of energy systems is the future control on carbon emissions. Emission constraints and the corresponding mechanisms, e.g. emissions trading schemes or carbon taxes, will lead to the fact that a price is assigned to carbon emissions. In the EU, e.g., an emission trading scheme has already been implemented. The future price of an emitted ton of CO_2 is uncertain and this uncertainty should be taken into account in the planning process.

Additional uncertainties are introduced by the liberalization of energy markets. Not being part of vertically integrated monopolies any more, power generators, e.g., have no longer the guarantee to recover all costs from energy consumers. Furthermore, the future price level in liberalized markets is unknown.

In view of the broad range and growing importance of uncertainties, investment decision makers need techniques for the quantification of such risks. Mean-variance portfolio theory is an adequate tool to take risks of investment projects into account and has been applied to several studies in the electric energy sector (see, e.g., [3]-[6]).

Inspired by the "Energy Hub" concept [7], which applies a multi-carrier greenfield layout as key approach, this paper extends and applies mean-variance portfolio theory to portfolios generating multi-energy outputs, e.g. electricity, heat and cooling power. By simultaneously considering various forms of energy during the planning process, this extension will enable an integrated long-term investment planning of energy systems . By this means, potentially exploitable synergies on the technical as well as economic level can be identified.

The remainder of this paper is structured as follows. Section 2 outlines the multi-energy model including the underlying assumptions. Section 3 presents an application of the model to an electricity and heat portfolio and section 4 concludes the paper.

2 The Multi-Energy Portfolio Model

2.1 Why Portfolio Theory?

Energy system planning means taking investment decisions, and investors being confronted with the uncertainty of unpredictable economic outcomes commonly use portfolio theory to manage risk and maximize portfolio return. In the former era, as generation portfolios of utilities were primarily composed of well established, technologically homogenous, fossil-fired generating assets, considering risk characteristics would not have changed investment decisions significantly [8]. When new fixed-cost technology options such as wind and PV are included, taking into account risk characteristics becomes imperative [9]. Furthermore, when added to a portfolio of relatively risky fossil fuel technologies, fixed-cost technologies will surprisingly reduce overall generating cost for any risk level, although their stand-alone kWh costs are higher. This means that today's energy system planners and policy makers should emphasize less the costs of individual generating technologies and more the costs of generating portfolios and strategies. Portfolio theory is an adequate tool to do so.

For utilities disposing of a certain generating portfolio, it may sometimes be impossible to realize within a short period of time an efficient portfolio resulting from portfolio analysis. However, portfolio-based energy system planning can reveal sensible directions to go to from today on. This aspect is also in line with the concept of the project "Vision of Future Energy Networks" [10], in the framework of which the work presented in this paper has been carried out. This project applies a so-called "greenfield approach" to energy systems, i.e. based on today's knowledge and possibilities a fictitious optimal system is built from scratch neglecting the current system structure. In a second step, the differences between the present situation and the desirable system are identified and ways how to realize this desirable system are demonstrated. On that score, portfolio theory is an appropriate method to determine how the optimal generation portfolio of the future could look like.

2.2 Fundamentals of Portfolio Theory

Before presenting the application to multi-energy generation portfolios, the mathematical foundations of portfolio theory will be stated shortly. Portfolio theory was developed in the early 1950s by Harry Markowitz, who published a paper about the selection of efficient financial portfolios [11]. He was the first to consider diversification as necessary for the construction of efficient portfolios and gave a first mathematical formalization of the idea of diversification in investments.

Portfolio theorists generally define a portfolio as a set of investments composed of securities. A security is simply a decision affecting the future. The totality of such decisions constitutes a portfolio [12]. Portfolio management aims at finding efficient portfolio mixes, i.e. its purpose is to maximize expected return for any given possible risk level.

Let P be a multi-security portfolio composed of n securities with $i \in [1, ..., n]$. The allocation vector $\mathbf{x_P}$[1] indicates the share (percentage) of security i in a portfolio P:

$$\mathbf{x_P} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \tag{1}$$

Portfolio theory uses two quantities to characterize a portfolio. The first one is the *expected return* R_P. Let $\mathbf{r}$ be the vector of expected returns of the individual securities:

$$\mathbf{r} = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_n \end{bmatrix} \tag{2}$$

With these definitions, the expected return of a portfolio can be calculated as the sum of the expected returns of the individual securities weighted by their respective share:

$$R_P = \sum_{i=1}^{n} x_i r_i = \mathbf{x_P}^T \cdot \mathbf{r} \tag{3}$$

[1] All vectors are represented in small letters and bold font.

The second number that is used for describing the performance of a portfolio is the *standard deviation* of its returns σ_P. The standard variation is a measure for the risk associated with holding a portfolio. If the individual security returns were independent variables, the portfolio standard deviation would simply be the weighted sum of all individual standard deviations. Security or asset prices, however, are generally dependent and thus correlated variables. A measure of the linear association between two variables is the *covariance*. The covariance matrix $\mathbf{\Sigma_P}$[2] contains the covariance values between the returns of any asset i with the returns of any other asset j for all $i, j \in [1, ..., n]$:

$$\mathbf{\Sigma_P} = \begin{bmatrix} \Sigma_{11} & \dots & \Sigma_{1n} \\ \vdots & \ddots & \vdots \\ \Sigma_{n1} & \dots & \Sigma_{nn} \end{bmatrix} \tag{4}$$

If i equals j, the covariance is simply the variance of asset i. By means of the covariance matrix, the variance of a portfolio can be calculated in the following way:

$$\sigma_P^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \Sigma_{ij} = \mathbf{x_P}^T \cdot \mathbf{\Sigma_P} \cdot \mathbf{x_P} \tag{5}$$

With equations 3 and 5, the following set of equations and inequations can be formulated:

$$\begin{array}{ll} (1.) & R_P = \sum_{i=1}^{n} x_i r_i \\ (2.) & \sigma_P^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \Sigma_{ij} \\ (3.) & \sum_{i=1}^{n} x_i = 1 \\ (4.) & x_1, ..., x_n \geq 0 \end{array} \tag{6}$$

With the help of these relations, the so-called efficient frontier can be calculated for various levels of returns by minimizing the Lagrangean function L:

$$L = \sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \Sigma_{ij} + \lambda_1 \left(\sum_{i=1}^{n} x_i r_i - R_P \right) + \lambda_2 \left(\sum_{i=1}^{n} x_i - 1 \right) \tag{7}$$

The efficient frontier indicates the points which offer the highest possible return for each possible amount of risk. Fig. 2 shows an efficient frontier (green line) for a simple two-assets example and points out the minimum variance portfolio. Given an investor's preferences (set of indifference curves), the optimal portfolio allocation $\mathbf{x_p^*}$ can be determined.

Another useful and descriptive number to describe the association between two variables is the *correlation coefficient* ρ_{ij}. It is calculated by dividing the covariance by the standard deviation of asset i and the standard deviation of asset j:

$$\rho_{ij} = \frac{cov_{ij}}{\sigma_i \sigma_j} \tag{8}$$

[2] All matrices are represented in capital letters and bold font.

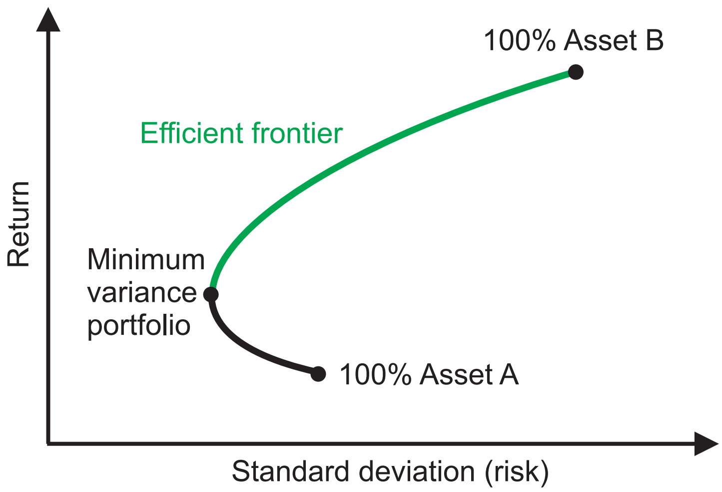

Figure 2: Efficient frontier for a two-assets example.

A correlation coefficient of +1 corresponds to a perfect positive linear relationship between the returns of asset i and j. If $\rho_{ij} = -1$, there is a perfect negative linear relationship between the two variables. If the variables are completely independent, the correlation coefficient is 0. The converse, however, does not hold true because the correlation coefficient detects only linear dependencies between two variables.

By diversifying a portfolio, i.e. by dividing investments into 2 or more assets that are less than perfectly correlated, one is able to reduce risk without reducing return at the same time. This is the so-called portfolio effect. Fig. 3 shows how the risk-return characteristic of a portfolio with two assets changes when the correlation coefficient increases from -1 to 1. It can be observed that a portfolio constructed with two assets, whose correlation coefficient equals 1, yields no portfolio effect because risk and return change linearly as the portfolio allocation changes from 100% of asset A to 100% of asset B. The lower is the correlation coefficient, the greater is the portfolio effect. If there is a decreasing linear relationship between assets A and B ($\rho = -1$), the investor has the possibility to construct a portfolio without risk.

2.3 Application and Extension to Multi-Energy Portfolios

Generation Technologies and Financial Assets: Analogies and Differences

To be able to apply portfolio theory to energy generation, one has to define the return of an energy generation technology. In conformity with the definition in the financial world, where expected return is the output (yield) divided by the input (cost), the return of a generation technology is defined

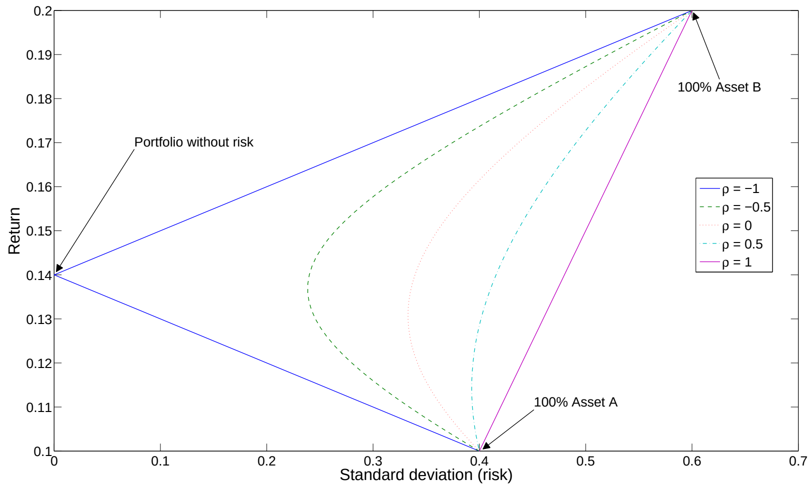

Figure 3: Risk and return of a two-assets portfolio as function of the correlation ρ_{12}.

as reciprocal value of the generation costs.[3] Return is thus expressed in "amount of energy per monetary unit".

Although this definition analogous to the one used in financial science may be sound, it should be noted that portfolio theory is based on several assumptions which may not strictly hold in the case of "real" generating assets. One difference, e.g., is that unlike financial assets, which are readily sellable, the liquidation of generating assets may be more difficult. Furthermore, the fact that power plants are non-dividable assets built in discrete size units may cause discontinuities in the portfolio allocation. For the analysis of large national portfolios, this may not pose significant problems. When analyzing portfolios containing exclusively small distributed generation technologies, the non-divisibility of production facilities may not be problematic even if the physical size of the portfolio is smaller.

Scenario-Based Portfolio Model

Usually the mean value and standard deviation of the expected return are derived by a time series analysis of historical data. Applying this ex-post point of view, one assumes that the past is a good "adviser" for the future and that by studying the past, it is possible to make inferences about the future. Experience, however, can become an unreliable guide for the future

[3]The analysis is based on costs and not on revenues from energy sales since from a societal point of view, it is appropriate to minimize costs and risks arising from energy production. If desired, it is possible to include revenues in the model. This would introduce the need to model further quantities, e.g. the evolution of the electricity price in the future.

especially in businesses where technology holds promise for dramatic change in the business environment [13]. In today's energy system environment, radical changes are ongoing and various factors, which have not existed before, strongly influence the evolution of energy systems. Among these factors are the liberalization process of energy industries and already established as well as expected regulations concerning CO_2 emissions. By relying on historical data, the influence and risks introduced by these relatively recent factors can not be taken into account. Furthermore, a significant number of new generation technologies are currently emerging. If one wants to include them in a portfolio analysis, it is obviously impossible to calculate means and variances from historical cost data since these are not yet existing.

In order to be able to derive efficient generation portfolios for the future taking into account recent developments, this paper proposes to calculate means and covariances of expected returns on the basis of a set of possible future scenarios instead of using historical data. As the evolution of the future energy system will be determined by a combination of external drivers and technological development, the set of scenarios will be defined on the basis of different possible states of these external drivers. External drivers can for instance be environmental concern regarding climate change, which has an effect on policy measures and thus on the price of CO_2 emissions, or geopolitical tensions, which have a bearing on prices of primary energy sources. Possible states - e.g. 'high', 'medium' and 'low' - are assigned to each of the drivers considered in the analysis. Depending on the number of drivers and possible states, a certain number of scenarios results. For example in the case of two drivers and three possible states, $3^2 = 9$ different scenarios result. In general, levelized generation costs of technologies will depend on the considered scenarios. If geopolitical tensions are high and prices of primary energy carriers increase, this will lead to an increase in the costs of generating technologies using natural gas or oil. The cost values can be summarized in the overall cost matrix $\mathbf{C_{tot}}$:

$$\mathbf{C_{tot}} = \begin{bmatrix} C_{11} & \cdots & C_{1s} \\ \vdots & \ddots & \vdots \\ C_{t1} & \cdots & C_{ts} \end{bmatrix} \tag{9}$$

with t being the number of technologies and s being the number of scenarios. This means that each column of the matrix $\mathbf{C_{tot}}$ corresponds to the generation costs of all considered technologies in a certain scenario.

$\mathbf{C_{tot}}$ represents the total cost of providing a certain amount of output energy. In general, this output can be any form of energy or a combination of these. In the case of a cogeneration technology, e.g., the corresponding value indicates the costs of providing a certain amount of electricity and heat. In the case of trigeneration, the cost of supplying cooling power would additionally be included. If one generally assumes a multi-energy generation portfolio providing a number of α energy output carriers and supposes that the costs for each technology generating more than one output energy can be allocated to the individual outputs, one obtains:

$$\mathbf{C_{tot}} = \sum_{i=1}^{\alpha} \mathbf{C_i} \tag{10}$$

Inverting the values in $\mathbf{C_{tot}}$ leads to the overall return matrix $\mathbf{R_{tot}}$:

$$\mathbf{R_{tot}} = \begin{bmatrix} \frac{1}{C_{11}} & \cdots & \frac{1}{C_{1s}} \\ \vdots & \ddots & \vdots \\ \frac{1}{C_{t1}} & \cdots & \frac{1}{C_{ts}} \end{bmatrix} = \begin{bmatrix} R_{11} & \cdots & R_{1s} \\ \vdots & \ddots & \vdots \\ R_{t1} & \cdots & R_{ts} \end{bmatrix} \tag{11}$$

with return being expressed in "amount of energy per monetary unit".

Individual probabilities of occurrence are assigned to each of the s scenarios. In this way, higher probabilities can be given to scenarios which are considered more likely to occur. The individual probabilities are gathered in the vector $\mathbf{p}$:

$$\mathbf{p} = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_s \end{bmatrix} \qquad \text{with} \qquad \sum_{i=1}^{s} p_i = 1 \tag{12}$$

By varying the probabilities assigned to the individual scenarios, one can carry out a sensitivity analysis in order to see how different assumptions about the future affect the portfolio choice. In this way, it is possible to determine robust portfolios that continue to be economical under a variety of uncertain future outcomes.

With the help of the overall return matrix $\mathbf{R_{tot}}$ and the probability vector $\mathbf{p}$, one can calculate the quantities needed for mean-variance portfolio analysis, namely the expected return of each technology and the covariance matrix. Using these quantities, one can compute the possible portfolio allocations and the corresponding efficient frontier according to equation 7.

Portfolios with Multi-Energy Outputs

When analyzing a multi-energy generation portfolio providing different energy outputs such as electricity, heat and cooling power or a chemical energy carrier like hydrogen, one is of course not only interested in costs and risks of a particular portfolio, but also in the share of the individual output energy carriers in the total energy output. For this purpose, the conversion efficiencies of each technology with respect to each output energy, e.g. the electric efficiency of a CHP plant, are taken and related to the overall efficiency of the converter.[4] The resulting value is the share of a certain energy output

[4]Conversion efficiencies are considered to be constant representing average values over the assumed lifetime of the plant.

in the overall energy output of one technology. For a certain technology i with a conversion efficiency η_{ik} with respect to the kth output energy and a total efficiency of $\eta_{i,tot}$, the share of output k in the total energy output of a converter is simply

$$\Gamma_{ik} = \frac{\eta_{ik}}{\eta_{i,tot}} \tag{13}$$

With the help of equation 13, one can define the *output ratio matrix* $\mathbf{\Gamma}$, which indicates for the whole set of technologies the share with respect to each of the α energy outputs:

$$\mathbf{\Gamma} = \begin{bmatrix} \Gamma_{11} & \cdots & \Gamma_{1t} \\ \vdots & \ddots & \vdots \\ \Gamma_{\alpha 1} & \cdots & \Gamma_{\alpha t} \end{bmatrix} \tag{14}$$

Multiplying $\mathbf{\Gamma}$ with the portfolio allocation vector $\mathbf{x_P} = \begin{bmatrix} x_1 & \cdots & x_t \end{bmatrix}^T$, which indicates the share of each technology in the overall portfolio, yields the portfolio energy carrier ratio $\mathbf{x_{out}}$:

$$\mathbf{x_{out}} = \begin{bmatrix} x_{out,1} \\ x_{out,2} \\ \vdots \\ x_{out,\alpha} \end{bmatrix} = \mathbf{\Gamma} \cdot \mathbf{x_P} \qquad \text{with} \qquad \sum_{k=1}^{\alpha} x_{out,k} = 1 \tag{15}$$

Lower and upper bounds on the values contained in $\mathbf{x_P}$ can be defined in order to account for planning constraints with respect to individual technologies. The vector $\mathbf{x_{out}}$ contains information about the share of each output energy carrier in the total output of the multi-energy portfolio. Using this information, a portfolio with the desired ratio between the different types of output energy can be chosen.

With this extension of mean-variance portfolio theory to multi-energy portfolios, it is possible to determine efficient portfolios, which provide an arbitrary number of energy outputs. Including the analysis of a set of possible scenarios, the presented model can be used as tool for an integrated long-term investment planning of future energy supply systems. Section 3 will present an application of the model to an electricity and heat generation portfolio.

3 Application Example: An Electricity and Heat Portfolio

In the following, the application of the general multi-energy portfolio model to a portfolio with two outputs - electricity and heat - will be presented. Furthermore, for the sake of clarity this application example is restricted to a set of small distributed generation technologies. The following technologies are included in the portfolio:

Technologies with electricity as output

- T1: Wind
- T2: Photovoltaics (PV)

Technologies with electricity and heat as output

- T3: Biogas engine
- T4: Natural gas fired engine

Technologies with heat as output

- T5: Solar (thermal)
- T6: Gas boiler

In a next step, a set of scenarios is defined. The differences between the scenarios come from different possible states of external drivers. The following three major drivers are assumed:

- D1: Environmental concern regarding climate change
- D2: Energy-related research efforts
- D3: Geopolitical tensions

D1 has an impact on policy measures with respect to climate change mitigation and thus on the price assigned to CO_2 emissions. D2 influences efficiency improvements especially of emerging generation technologies and D3 has an effect on prices of primary energy sources. Each of the three drivers can have two different states - 'high' or 'low'. The possible combinations of the states of the drivers, i.e. high/low environmental concern, high/low energy-related research efforts and high/low geopolitical tensions, result in the $2^3 = 8$ different scenarios shown in table 1.

Table 1: Scenario definition.

Scenarios	S1	S2	S3	S4	S5	S6	S7	S8
D1	high	high	high	high	low	low	low	low
D2	high	high	low	low	high	high	low	low
D3	high	low	low	high	high	low	low	high

In each of the scenarios, the socio-technical environment as well as the economic conditions of the energy system and consequently also the generation costs of technologies will be different. Cost data for electricity and cogeneration technologies from the NEA/IEA report ”Projected Costs of Generating Electricity” [14] as well as data for heat generating technologies from [15] serves as a basis for the formulation of scenarios. The cost values are in many cases strongly dependent on specific local realities. The levelized costs of a PV plant, e.g., highly depend on the average radiation intensity at the plant location and costs of wind power plants are above all determined by the average on-site wind speed. Hence the purpose of this application example is not to derive an efficient generation portfolio with general validity, but to illustrate the principle of the proposed method.

The data from [14] and [15] are considered to correspond to scenario S7, where the state of all drivers is ’low’. Starting from this base scenario, the remaining scenarios are built by adjusting the levelized generation costs according to the state of each driver.

Strong environmental concern (D1 ’high’) will result in a certain price for carbon emissions and lead to an increase in generation costs of technologies generating CO_2, which are in this case the natural gas fired engine (T4) and the gas boiler (T6). With an assumed CO_2 price of 30 USD/t and the respective emission intensity factors, the change in generation costs for T4 and T6 can be calculated. As the other technologies feature no net CO_2 emissions, their costs remain unaffected by a CO_2 price.

Intensive energy-related research efforts (D2 ’high’) will lead to efficiency improvements above all in the case of emerging technologies like PV, thermal solar panels and biogas engines. Efficiency improvements and the resulting cost reductions for other technologies are assumed to be smaller depending on their maturity level.

Last but not least, high geopolitical tensions (D3 ’high’) can lead to higher prices of primary energy carriers. As in the case of a price for CO_2, this only affects the fuel costs of T4 and T6 since the other technologies do not use fossil fuels to produce energy.

With the scenarios defined in table 1, one obtains the following cost matrices for the electricity and heat output:

$$\mathbf{C_{el}} = \begin{bmatrix} 43.3 & 43.3 & 44.2 & 44.2 & 43.3 & 43.3 & 44.2 & 44.2 \\ 253.3 & 253.3 & 287.8 & 287.8 & 253.3 & 253.3 & 287.8 & 287.8 \\ 59.9 & 59.9 & 63.0 & 63.0 & 59.9 & 59.9 & 63.0 & 63.0 \\ 81.4 & 64.7 & 66.0 & 83.0 & 77.8 & 61.2 & 62.4 & 79.4 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{16}$$

and

$$\mathbf{C_{heat}} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 11.4 & 11.4 & 12.0 & 12.0 & 11.4 & 11.4 & 12.0 & 12.0 \\ 31.2 & 25.6 & 26.1 & 31.7 & 27.8 & 22.2 & 22.7 & 28.4 \\ 13.2 & 13.2 & 14.7 & 14.7 & 13.2 & 13.2 & 14.7 & 14.7 \\ 16.8 & 13.9 & 14.0 & 17.0 & 10.4 & 7.5 & 7.6 & 10.6 \end{bmatrix} \tag{17}$$

with the unit of all cost values being USD/MWh.

The total cost matrix $\mathbf{C_{tot}}$ and the total return matrix $\mathbf{R_{tot}}$ are calculated according to equation 10 and 11. It is assumed that all scenarios have equal probabilities of occurrence, i.e.:

$$p_i = 0.125 \qquad \forall i = 1, ..., 8 \tag{18}$$

Furthermore, the thermal and electric efficiencies of the cogeneration technologies result in the following output ratio matrix for this example:

$$\mathbf{\Gamma} = \begin{bmatrix} 1 & 1 & 0.39 & 0.49 & 0 & 0 \\ 0 & 0 & 0.61 & 0.51 & 1 & 1 \end{bmatrix} \tag{19}$$

With these data and parameters, the share of electricity and heat can be determined for any possible portfolio allocation. Fig. 4 indicates for each combination of risk and return the corresponding electricity share, i.e. the part electricity production has in the total energy production within the portfolio.

One observes that portfolios with a high electricity share show low risk at low returns or high production costs respectively. Wind and PV, which are the technologies producing only electricity, are not affected by uncertainties regarding fuel or CO_2 prices, which explains the low standard deviation of portfolios with a high share of electricity. Since the exergy, i.e. the energetic quality, of 1 MW of electricity is higher than that of 1 MW of heat, the returns of portfolios with a low electricity and a high heat share are consequently higher. The average production costs of PV, which are by far the highest of all technologies, further amplify this effect.

Fig. 5 shows the same type of diagram for the heat share. Since the sum of electricity and heat share is equal to 1 for each risk-return combination, the heat share is low for points with a high electricity share and vice versa. By means of this type of diagrams, the system planner can choose an efficient mix of generation technologies, which corresponds to his degree of risk aversion and for which the outputs - in this case electricity and heat - have the desired ratio.

The resulting efficient frontier, i.e. the points featuring the highest possible return for each possible risk level, is computed according to equation 7 and depicted in Fig. 6.

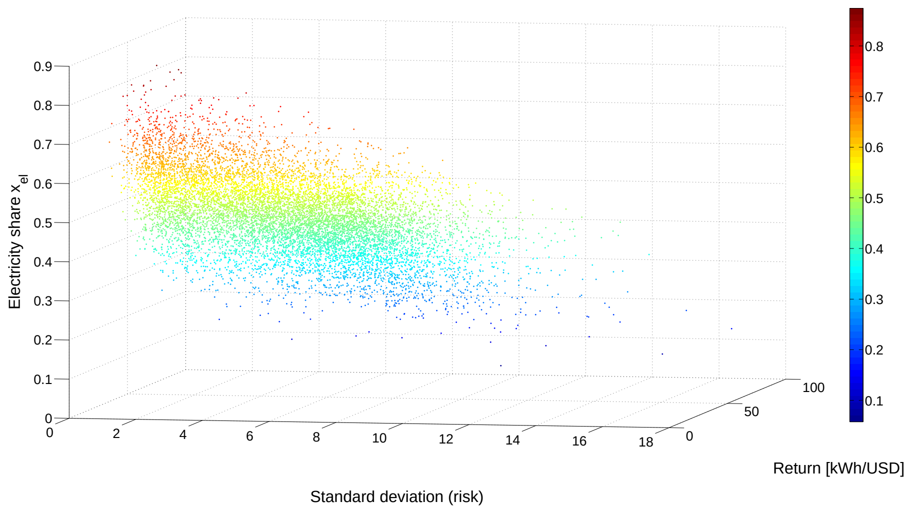

Figure 4: Share of electricity in the combined electricity and heat portfolio as function of risk and return.

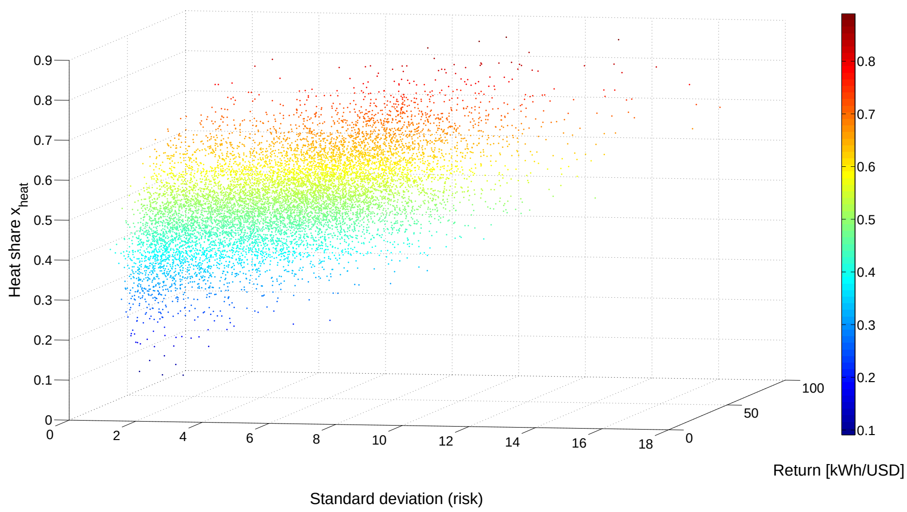

Figure 5: Share of heat in the combined electricity and heat portfolio as function of risk and return.

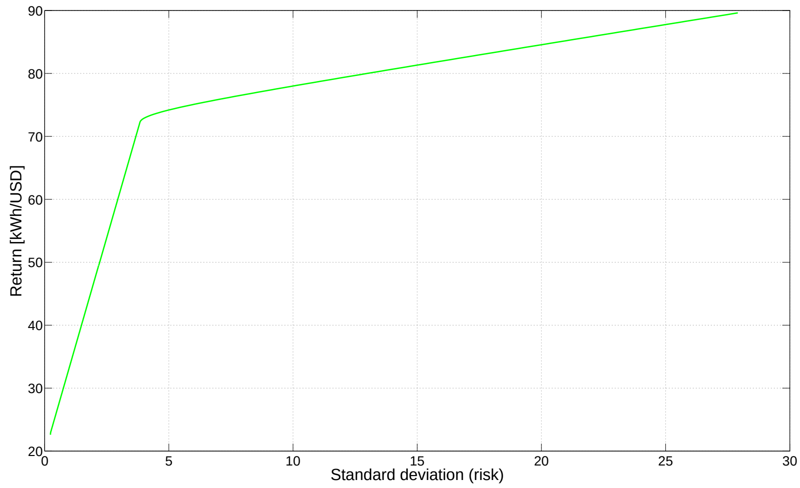

Figure 6: Efficient frontier of the combined electricity and heat portfolio.

The efficient frontier indicates the points featuring the highest return for each possible risk level regardless of the shares of the individual outputs in the overall portfolio output. It may therefore occur that no portfolio on the efficient frontier can fulfill the planning requirements concerning the ratio between the energy outputs. In order to check the physical feasibility of a portfolio, the shares of electricity and heat along the efficient frontier are calculated and illustrated in Fig. 7.

One can see that, in the case of this example, any electricity or heat share between 0 and 1 is realizable. The highest electricity shares result for portfolios with low risk, whereas the heat share rises with increasing risk. The majority of the portfolios on the efficient frontier only produce heat. If the portfolio analysis results in an efficient frontier that does not include any point allowing to realize the desired ratio between the output energy carriers, one has to choose an "inefficient" point. In such a case, the economic performance of the portfolio would be limited by physical planning requirements.

Eventually, Fig. 8 shows which technologies constitute the portfolios lying on the efficient frontier. In this application example electricity production solely comes from wind power plants, whereas PV and the two cogeneration technologies do not contribute to the efficient frontier. Portfolios providing both electricity and heat are made up almost exclusively by wind and solar panels. Only with increasing risk the share of gas boilers goes up.

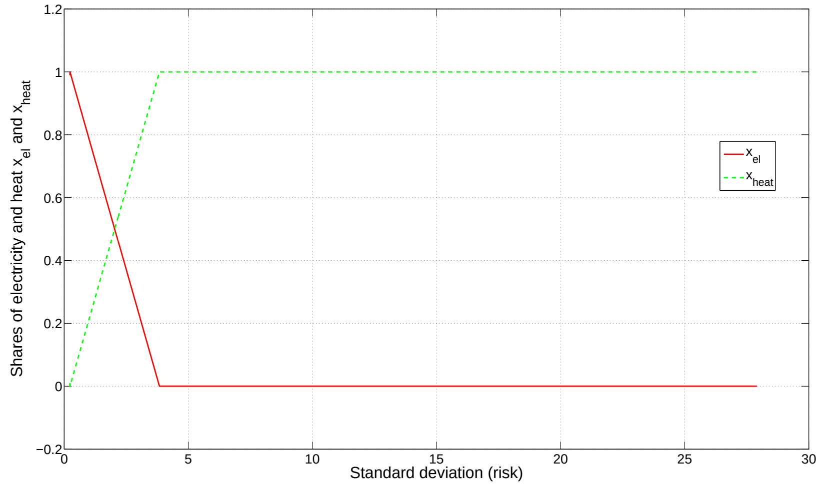

Figure 7: Shares of electricity and heat along the efficient frontier.

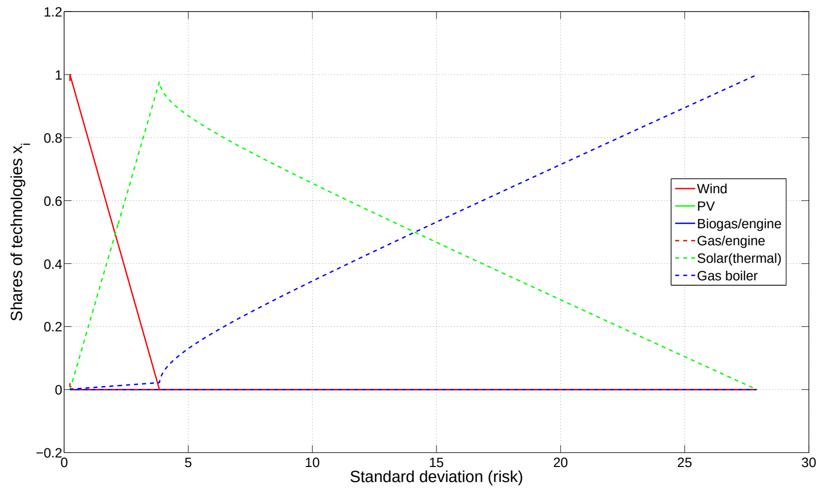

Figure 8: Shares of all technologies along the efficient frontier.

4 Conclusion

This paper presented the application of mean-variance portfolio theory to multi-energy portfolios. Mean-variance portfolio theory had already been applied to electricity generation portfolios. The model stated in this paper is a general extension of this application and enables an integrated assessment of portfolios generating multi-energy outputs such as electricity, heat, cooling, etc. Using a set of several possible scenarios, the model allows to appropriately incorporate uncertainties about future developments that can alter the economic performance of the considered generation technologies. By assigning individual probabilities of occurrence to the different scenarios and by analyzing them in an integrated way, energy system planners can determine a portfolio being the best answer to a set of possible future developments as a whole instead of having to choose a portfolio being only efficient for one single scenario. In this way the model provides a useful tool to derive efficient multi-energy generation portfolios for the future and thus provides valuable support for investment decision makers.

Acknowlegdements

The authors would like to thank ABB, Areva, Siemens, and the Swiss Federal Office of Energy for supporting the research project "Vision of Future Energy Networks", as well as the other members of the project team for inspiring discussions.

References

[1] IEA. World Energy Outlook. 2005.

[2] IEA. World Energy Outlook. 2006.

[3] D. Bar-Lev and S. Katz. A portfolio approach to fossil fuel procurement in the electric utility industry. *Journal of Finance*, 31(3):933–947, 1976.

[4] E. G. Domingues, H. Arango, J. Policarpo G. A., C. B. Campinho, and G. Paulillo. Applying modern portfolio theory to investment projects in electric energy markets. In *IEEE Power Tech*, Porto, 2001.

[5] S. Awerbuch and M. Berger. Applying portfolio theory to EU electricity planning and policy-making. *IEA/EET Working Paper*, 2003.

[6] B. Krey and P. Zweifel. Efficient electricity portfolios for Switzerland and the United States. *Working Paper No. 0602*, 2006.

[7] M. Geidl, G. Koeppel, P. Favre-Perrod, B. Klöckl, G. Andersson, and K. Fröhlich. Energy hubs for the future. *IEEE Power and Energy Magazine*, 5(1):24–30, 2007.

[8] S. Awerbuch. The surprising role of risk in utility integrated resource planning. *The Electricity Journal*, 6(3):20, 1993.

[9] A. B. Lovins et al. *Small is profitable: the hidden economic benefits of making electrical resources the right size.* Rocky Mountain Institute, 2002.

[10] M. Geidl, P. Favre-Perrod, B. Klöckl, and G. Koeppel. A greenfield approach for future power systems. In *Cigre Session 41*, Paris, France, 2006.

[11] H. M. Markowitz. Portfolio selection. *Journal of Finance*, 7(1):77–91, 1952.

[12] W. F. Sharpe. *Portfolio theory and capital markets*. McGraw-Hill, 1999.

[13] K. B. Leggio, D. L. Bodde, and M. L. Taylor. *Managing enterprise risk - What the electric industry experience implies for contemporary business*. Elsevier, 2006.

[14] NEA and IEA. *Projected costs of generating electricity*. 2005.

[15] U. Ganter et al. Perspektiven der zukünftigen Strom- und Wärmeversorgung für die Schweiz. *PSI Bericht Nr. 01-12*, 2001.