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Comprehensive Performance and Incertitude Analysis of Multi-Energy Portfolios

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***Abstract*—In this paper a model for the assessment of efficient energy generation portfolios is presented. The total energy output can consist of multiple energy carriers such as electricity, heat or chemical energy carriers. In order to take into account multiple aspects of performance and different types of incertitude influencing the long-term energy planning process, two different methods are combined. Mean-variance portfolio theory and multi-criteria diversity analysis are applied resulting in a multi-objective optimization problem. Solving this optimization problem for multi-energy portfolios allows for identifying energy generation technologies mixes that both minimize the exposure to various kinds of incertitude and maximize performance with respect to multiple performance criteria. In this way multi-energy portfolios are analyzed in a comprehensive and systematic way.**

***Index Terms*—Energy system planning, cogeneration, multiple energy carriers, mean-variance portfolio theory, multi-criteria diversity analysis, multi-objective optimization.**

I. Introduction

THE project "Vision of Future Energy Networks" at ETH Zurich applies a greenfield approach to the design of future power systems [1]. Multiple energy carriers, e.g. electricity, heat and chemical energy, are considered in the approach in order to be able to exploit synergies and to utilize complementary characteristics of different energy carriers. When thinking about prospective structures for such systems, it is essential to have knowledge about potential options for the future energy supply.

Applying a long-term perspective to the planning of future energy supply involves conditions of decision making that are characterized by different kinds of incertitude. Following the concept presented in [2], the full spectrum of incertitude can be represented as illustrated in Fig. 1. Depending on the knowledge about possible outcomes and the associated probabilities, a distinction is made between risk, uncertainty, ambiguity and ignorance. In [3] a model considering only risk is introduced. It applies mean-variance portfolio (MVP) theory to multi-energy generation portfolios assuming that probabilities can be assigned to scenarios representing a set of well-defined possible outcomes. However, the model neglects the three other types of incertitude mentioned above. In [4] Stirling presents the so-called multi-criteria diversity analysis (MDA) being a concept measuring diversity and performance based on multiple criteria. Conceiving incertitude as reciprocal of multi-criteria diversity, this concept covers the space of uncertainty, ambiguity and ignorance. MDA, however, does not exploit information in the risk space.

		Knowlegde about outcomes	
		Well-defined outcomes	Poorly-defined outcomes
Knowlegde about probabilities		*Type of incertitude*	
	Some basis for probabilites	Risk	Ambiguity
	No basis for probabilites	Uncertainty	Ignorance

Fig. 1. Knowledge about probabilities and outcomes and the associated types of incertitude after [2].

With respect to performance criteria, MVP uses only economic quantities such as levelized energy generation costs for measuring the portfolio performance. In contrast, MDA defines performance as function of multiple criteria. Applying the MDA framework thus allows to simultaneously consider the economic, environmental and social dimensions of sustainability in the analysis by defining appropriate performance criteria as well as the corresponding weights assigned to these criteria. Furthermore, technical performance aspects can be taken into account explicitly.

In order to overcome the limitations of both MVP and MDA and to cover the full spectrum of incertitude, their combined application has been proposed in [5]. In this paper, we take up the approach from [5], formulate a multi-objective optimization problem incorporating both MVP and MDA quantities in a single objective function, and extend the model for the purpose of analyzing portfolios generating multiple energy carriers. Following this approach, the paper provides a model for comprehensive performance and incertitude analysis of multi-energy portfolios.

II. Modelling and optimization

In this section, both the MVP and the MDA model are described. Furthermore, their combined application using multi-objective optimization as well as the modelling framework for multi-energy portfolios is outlined.

A. The mean-variance portfolio model

Common applications of mean-variance portfolio theory use historical data for the calculation of expected returns and correlations (see, e.g., references [6]-[9]). In contrast to these approaches based on historical time series of cost

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data, the MVP model presented in this paper pursues an ex-ante approach. In order to be able to determine efficient generation portfolios considering present-day developments and associated expectations for the future, the model uses a set of scenarios for the future instead of historical data to calculate means and covariances of expected returns. Expected returns, which are defined as reciprocal of levelized energy generation costs, depend on the considered scenarios. In a scenario with, e.g., a high CO_2 price, energy generation costs of technologies using fossil fuels will be correspondingly higher. Influence factors such as the CO_2 price are considered to be external factors having the potential to affect energy generation costs. In the MVP model, external factors can take different discrete states, e.g. 'high', 'medium' and 'low'. For each possible combination of states of external factors, the energy generation costs of the whole set of technologies are calculated. This yields the cost matrix $\mathbf{C_{MVP}}$:

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

The rows of $\mathbf{C_{MVP}}$ indicate the energy generation costs of a certain technology in each of the s scenarios; the columns contain the cost values for each of the t technologies in a particular scenario. Calculating the reciprocal of each value in $\mathbf{C_{MVP}}$ gives the return matrix $\mathbf{R_{MVP}}$ which thus contains the expected returns of all t technologies in each of the s scenarios:

$$\begin{aligned} \mathbf{R_{MVP}} &= \begin{bmatrix} \frac{1}{C_{MVP,11}} & \cdots & \frac{1}{C_{MVP,1s}} \\ \vdots & \ddots & \vdots \\ \frac{1}{C_{MVP,t1}} & \cdots & \frac{1}{C_{MVP,ts}} \end{bmatrix} \\ &= \begin{bmatrix} R_{MVP,11} & \cdots & R_{MVP,1s} \\ \vdots & \ddots & \vdots \\ R_{MVP,t1} & \cdots & R_{MVP,ts} \end{bmatrix} \end{aligned} \tag{2}$$

This means that return is measured in units of generated energy per unit of money expenditure.

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

$$\mathbf{p_{MVP}} = \begin{bmatrix} p_{MVP,1} \\ p_{MVP,2} \\ \vdots \\ p_{MVP,s} \end{bmatrix} \quad \text{with} \quad \sum_{k=1}^{s} p_{MVP,k} = 1 \tag{3}$$

With the (t, 1)-dimensional allocation vector $\mathbf{x}$ indicating the share of each technology in the overall portfolio, the portfolio return r_{MVP} becomes:

$$r_{MVP} = \mathbf{x^T} \cdot \mathbf{R_{MVP}} \cdot \mathbf{p_{MVP}} \tag{4}$$

The standard deviation σ_{MVP} being a measure for the portfolio risk can be calculated as follows:

$$\sigma_{MVP} = \sqrt{\mathbf{x^T} \cdot \mathbf{\Sigma_{MVP}} \cdot \mathbf{x}} \tag{5}$$

with $\mathbf{\Sigma_{MVP}}$ being the covariance matrix. The elements of $\mathbf{\Sigma_{MVP}}$ are calculated by means of $\mathbf{R_{MVP}}$ and $\mathbf{p_{MVP}}$:

$$\Sigma_{MVP,ij} = \sum_{k=1}^{s} \Delta_{ik} \cdot \Delta_{jk} \cdot p_{MVP,k} \tag{6}$$

where Δ_{ik} is the difference between $R_{MVP,ik}$, i.e. the return of technology i in scenario k, and $\bar{R}_{MVP,i}$ being the expected return of technology i over all scenarios.

Using (4) and (5), the MVP efficient frontier can be determined by solving the following optimization problem: For feasible values of the portfolio return r_{MVP}:

$$\text{Minimize}: \quad \sigma^2_{MVP} = \mathbf{x^T} \cdot \mathbf{\Sigma_{MVP}} \cdot \mathbf{x} \tag{7}$$

subject to the constraints

$$x_i \geq 0 \quad \forall\ i\ \in\ [1, ..., t] \tag{8a}$$

$$\sum_{i=1}^{t} x_i = 1 \tag{8b}$$

where x_i is the share of technology i in the portfolio.

B. The multi-criteria diversity analysis framework

In contrast to the MVP model, where economic quantities, namely levelized generation costs, are the only measure for portfolio return, the MDA framework comprehends performance in a broader sense. Portfolio performance is defined as function of multiple performance criteria and calculated as:

$$g_{MDA} = \mathbf{x^T} \cdot \mathbf{G_{MDA}} \cdot \mathbf{w_{MDA,perf}} \tag{9}$$

where $\mathbf{G_{MDA}}$ is a (t, n_{perf})-dimensional matrix with n_{perf} being the number of performance criteria. Each value $G_{i,j}$ in $\mathbf{G_{MDA}}$ is a normalized performance measure ($0 \leq G_{i,j} \leq 1$) expressing the performance of technology i with respect to performance criterion j. The (n_{perf}, 1)-dimensional vector $\mathbf{w_{MDA,perf}}$ contains the relative weights given to each performance criterion. The possibility to include multiple performance criteria allows for extending the analysis from a purely cost-based perspective to, e.g., a sustainability-oriented perspective aiming at meeting economic, environmental and social criteria. Furthermore, criteria relating to technical characteristics of energy generation technologies can be explicitly taken into account. Such technical criteria may comprise the operational flexibility of power plants and the intermittency of energy generation.

MDA conceptualizes diversity as a direct means to deal with uncertainty, ambiguity and ignorance. A main aspect of diversity are the disparities between technologies. The concept of disparity makes use of those attributes which are considered to represent essential differences between technologies. Such an attribute can, e.g., be the ease of integration of a technology into buildings. The (t, n_{disp})-dimensional matrix $\mathbf{A_{MDA}}$ gathers the normalized values of each disparity attribute with regard to each technology. If a technology can, e.g., be easily integrated into buildings, the corresponding value of the disparity attribute would be 1. By means of $\mathbf{A_{MDA}}$ and the vector $\mathbf{w_{MDA,disp}}$ containing the relative weights given to each disparity attribute, the disparity matrix $\mathbf{D_{MDA}}$ is determined. The values $D_{MDA,ij}$ in $\mathbf{D_{MDA}}$ are the Euclidian distances between technologies i and j in the disparity space and are calculated as:

$$D_{MDA,ij} = \sqrt{\sum_{k=1}^{n_{disp}} (a_{i,k} - a_{j,k})^2} \qquad (10)$$

where n_{disp} is the number of disparity attributes and $a_{i,k}$ is the weighted disparity value of technology i with respect to attribute k.

MDA portfolio incertitude, the analogous quantity to risk in MVP, is defined as reciprocal of the portfolio diversity d_{MDA}:

$$I_{MDA} = \frac{1}{d_{MDA}} = \frac{1}{\mathbf{x^T} \cdot \mathbf{D_{MDA}} \cdot \mathbf{x}} \qquad (11)$$

Using the equations defined above, the MDA efficient frontier can be calculated as follows:

For feasible values of the portfolio performance g_{MDA}:

$$\text{Minimize}: \quad I_{MDA} = \frac{1}{\mathbf{x^T} \cdot \mathbf{D_{MDA}} \cdot \mathbf{x}} \qquad (12)$$

subject to the constraints

$$x_i \geq 0 \quad \forall\, i \,\in\, [1, ..., t] \qquad (13a)$$

$$\sum_{i=1}^{t} x_i = 1 \qquad (13b)$$

C. Combined application of MVP and MDA

Instead of calculating separate MVP and MDA efficient frontiers, both methods are combined in order to cover all types of incertitude in long-term energy planning. We extend the approach presented in [5] and formulate a multi-objective optimization problem using the technique of minimizing a single aggregate objective function being the weighted linear sum of the objectives. The resulting optimization problem to calculate the comprehensive efficient frontier considering both MVP risk and MDA incertitude is the following:

For a given value of Ψ ($0 \leq \Psi \leq 1$) and for feasible values of the total portfolio performance G_{tot}:

$$\text{Minimize}: \quad I_{tot} = \Psi \cdot \sigma_{MVP,norm} + (1 - \Psi) \cdot I_{MDA,norm} \qquad (14)$$

subject to the constraints

$$x_i \geq 0 \quad \forall\, i \,\in\, [1, ..., t] \qquad (15a)$$

$$\sum_{i=1}^{t} x_i = 1 \qquad (15b)$$

where the factor Ψ expresses the weight given to MVP, $\sigma_{MVP,norm}$ and $I_{MVP,norm}$ are the normalized[1] MVP risk and MDA incertitude, respectively. I_{tot} is the total incertitude and x_i is the share of technology i in the portfolio.

Using this multi-objective optimization procedure, the method allows the determination of efficient portfolios that minimize the exposure to the whole spectrum of incertitude and maximize performance with respect to multiple criteria.

D. Modelling framework for multi-energy portfolios

Energy consumers demand different energy carriers such as electricity, heat and natural gas. In order to meet the future energy demand in an optimal way, energy system planning should take account of multiple energy carriers. This approach offers potential benefits like the exploitation of synergies and the increase of energy supply efficiency. Furthermore, making use of conversion possibilities between different energy carriers results in increased operational flexibility.

To be able to apply the method presented in this paper to portfolios providing multiple energy outputs, a number of modelling extensions are made. The conversion efficiencies of each technology with respect to each output energy, e.g. the electric efficiency of a CHP plant, are related to the overall efficiency of the converter.[2] The resulting value is the share of a certain energy output in the overall energy output of one technology. For a technology i having a conversion efficiency η_{ki} with respect to output energy k and a total efficiency of $\eta_{i,tot}$, the share of output k in the total energy output of a converter is:

$$\Gamma_{ki} = \frac{\eta_{ki}}{\eta_{i,tot}} \qquad (16)$$

With (16), 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, is defined:

$$\mathbf{\Gamma} = \begin{bmatrix} \Gamma_{11} & \cdots & \Gamma_{1t} \\ \vdots & \ddots & \vdots \\ \Gamma_{\alpha 1} & \cdots & \Gamma_{\alpha t} \end{bmatrix} \qquad (17)$$

Multiplying $\mathbf{\Gamma}$ with the portfolio allocation vector $\mathbf{x}$ yields the portfolio energy carrier ratio $\mathbf{x_{out}}$:

$$\mathbf{x_{out}} = \begin{bmatrix} x_{out,1} \\ x_{out,2} \\ \vdots \\ x_{out,\alpha} \end{bmatrix} = \mathbf{\Gamma} \cdot \mathbf{x} \quad \text{with} \quad \sum_{k=1}^{\alpha} x_{out,k} = 1 \qquad (18)$$

The values $x_{out,k}$ are the shares of each output energy k in the total output of the multi-energy portfolio. Using (18) as additional constraint in the multi-objective portfolio optimization, portfolios providing the desired quantity of each output energy carrier are determined.

III. Application Example

In general the above presented multi-energy portfolio model combining MVP and MDA is applicable to an arbitrary number of energy outputs. In this section, the example of a portfolio providing 50% electricity and 50% heat is presented. The considered set of technologies is the following:

Technologies with electricity as output

- T1: Wind

[1] The normalized value q_{norm} of a quantity q is calculated as: $q_{norm} = \frac{q - min[q]}{max[q] - min[q]}$

[2] The values for conversion efficiencies can, e.g., be chosen as average values over the assumed lifetime of the power plants. If available, more detailed information can be included in the analysis.

- T2: Small hydro
- T3: Photovoltaics (PV)
- T4: Fuel cell fired by natural gas

Technologies with electricity and heat as output

- T5: Internal combustion engine fired by biogas
- T6: Internal combustion engine fired by natural gas

Technologies with heat as output

- T7: Solar thermal collector
- T8: Gas boiler

The set of scenarios used in the scenario-based MVP model is derived taking into account the influence of the following external factors:

- F1: Cost of CO_2 arising from carbon constraints
- F2: Efficiency gains from energy-related research efforts
- F3: Price of fossil fuels

Each of these factors can take two different levels - 'high' or 'low'. All possible combinations of states of external factors result in the set of scenarios shown in Table I.

TABLE I
SCENARIOS AND EXTERNAL FACTORS.

Scenarios	S1	S2	S3	S4	S5	S6	S7	S8
F1	high	high	high	high	low	low	low	low
F2	high	high	low	low	high	high	low	low
F3	high	low	low	high	high	low	low	high

The cost data corresponding to the scenarios are given in Appendix A. In order to determine the return matrix $\mathbf{R_{MVP}}$ needed as input for the MVP part of the analysis, the reciprocals of the cost data values are calculated. Another input for the MVP analysis is the probability vector $\mathbf{p_{MVP}}$ containing the probability values of all scenarios. In this generic application example, equal probabilities for all scenarios are assumed, i.e. $p_{MVP,i} = 0.125 \; \forall i = 1, ..., 8$. In a specific application case, appropriate probability values reflecting available information and estimates about future developments of external factors will be assigned.

For the MDA part of the analysis, the following performance criteria are considered: Cost performance, environmental performance, public acceptance, long-term security, and system operation. While the latter relates to technical characteristics like contribution to power system stability, the other criteria comprehend the economic, environmental and social aspects of sustainability.

The disparity attributes considered in this application example are the following: Physical form of the primary energy resource (fossil fuel or renewable), ease of building integration, CHP generation, output controllability, subject to CO_2 regulations (yes or no), and level of maturity of the technology.

The numerical values for the MDA part of the analysis, i.e. the performance matrix $\mathbf{G_{MDA}}$, the weight vector $\mathbf{w_{MDA,perf}}$, the disparity matrix $\mathbf{A_{MDA}}$ and the weight vector $\mathbf{w_{MDA,disp}}$, are provided in Appendix B.

The electric and thermal efficiencies of the cogeneration technologies result in the following output ratio matrix $\mathbf{\Gamma}$:

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

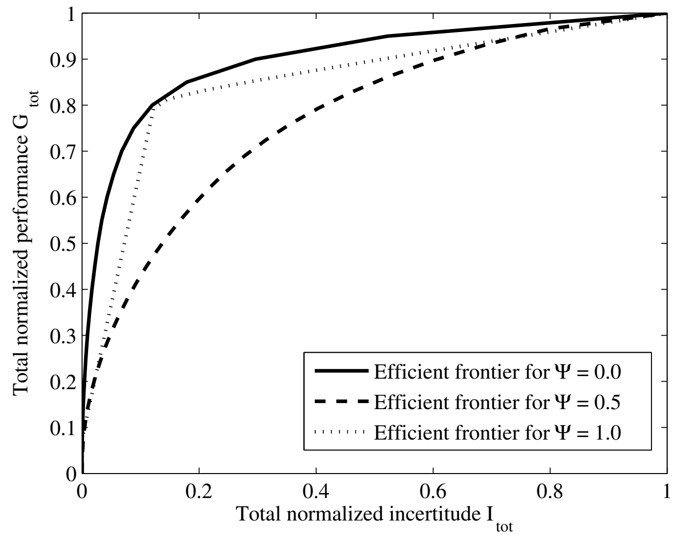

Fig. 2. Efficient frontiers for different values of the weighting factor Ψ.

As the portfolio shall provide 50% electricity and 50% heat, the portfolio energy carrier ratio $\mathbf{x_{out}}$ is:

$$\mathbf{x_{out}} = \begin{bmatrix} 0.5 & 0.5 \end{bmatrix}^T \quad (20)$$

In order to calculate comprehensive efficient frontiers and the corresponding portfolio allocations for this application example, the optimization problem (14) is solved for the given input data. In doing so, (20) is used as additional constraint in (15).

Fig. 2 shows simulation results of a sensitivity analysis with respect to the weighting factor Ψ. Efficient frontiers indicating Pareto optimal performance-incertitude combinations have been calculated for $\Psi = 1$ (pure MVP analysis), $\Psi = 0.5$ (equal weights given to MVP and MDA) and $\Psi = 0$ (pure MDA analysis). The three curves in Fig. 2 indicate the maximum level of total normalized performance G_{tot} at each level of total normalized incertitude I_{tot} for the chosen values of Ψ.

Fig. 3 shows the portfolio allocations on the purely MVP-based efficient frontier ($\Psi = 1$). At all levels of total incertitude, the portfolios exhibit a low degree of diversification. The maximum number of technologies forming a portfolio is three. At the extreme ends of the incertitude range, only two technologies are present in the portfolio - the biogas engine and small hydro at minimum incertitude, and the gas boiler and and small hydro at maximum incertitude. The low degree of diversification can be explained by the fact that the correlation between expected returns of certain technologies is relatively high. Therefore, diversification does not lead to a significant reduction of incertitude resulting in portfolios with a limited number of technologies.

Fig. 4 presents the portfolio allocations on the efficient frontier for $\Psi = 0.5$. At low incertitude levels, the portfolios consist of five technologies, i.e. the degree of diversification is higher than in the case of $\Psi = 1$. With increasing incertitude, the degree of diversification decreases because the high number of technologies accompanied by low incertitude levels is substituted with a limited number of technologies

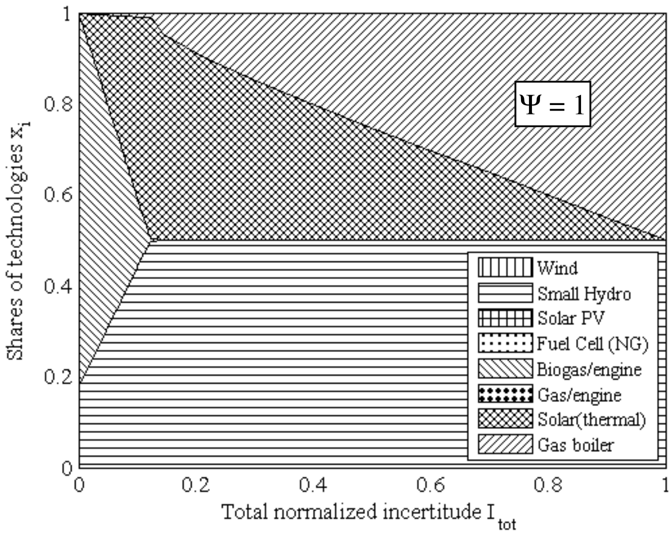

Fig. 3. Portfolio allocations on the efficient frontier for $\Psi = 1.0$ (whole weight assigned to MVP analysis).

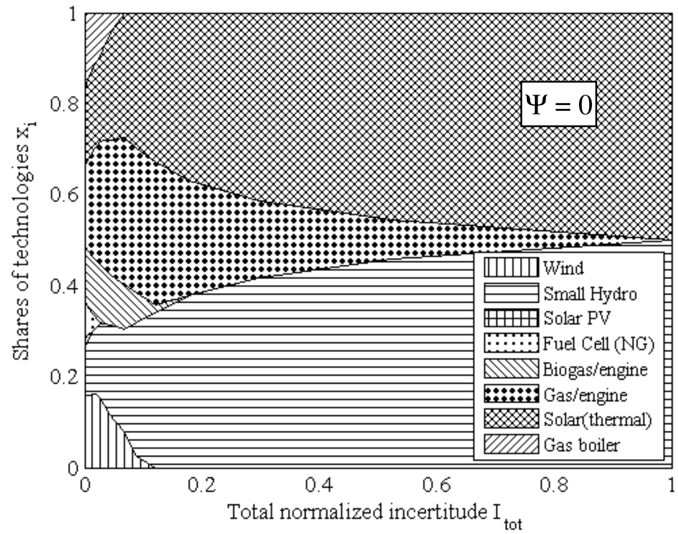

Fig. 5. Portfolio allocations on the efficient frontier for $\Psi = 0.0$ (whole weight assigned to MDA).

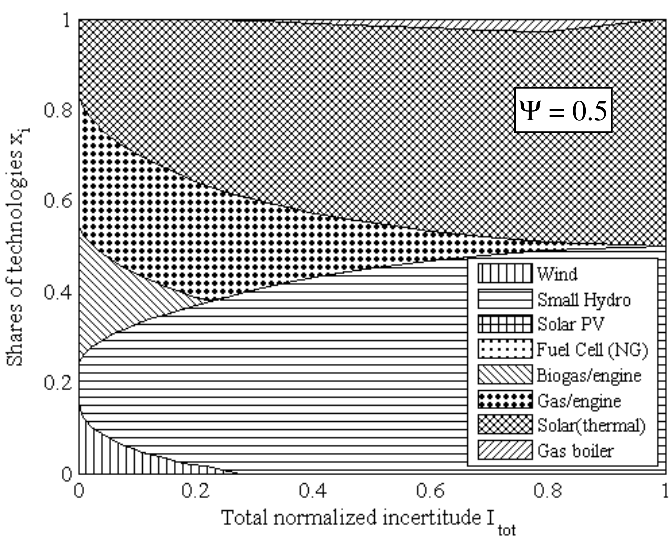

Fig. 4. Portfolio allocations on the efficient frontier for $\Psi = 0.5$ (half of the weight assigned to MVP analysis and half of the weight given to MDA).

providing high performance values. Solar thermal collectors and small hydro provide the highest performance in the case of $\Psi = 0.5$ given the criteria weightings chosen in this application example.

The portfolio allocations for the case $\Psi = 0.0$ are represented in Fig. 5. It can be seen that assigning the complete weight to the MDA analysis results in the highest degree of diversification at low incertitude levels. At an incertitude level of $I_{tot} = 0$, the complete set of technologies contributes to the portfolio. As in the case of equal weights assigned to MVP and MDA ($\Psi = 0.5$), diversification decreases with increasing incertitude levels implying high performance levels.

A comparison of the three cases shows that the efficient frontiers and the corresponding choices of technology options depend on the weight given to the MVP and MDA part of the analysis. The weighting factor Ψ can be adjusted according to the confidence in cost projection scenarios and the importance assigned to performance criteria other than cost. In this respect, the model presented in this paper represents a flexible planning tool for future multi-energy portfolios.

IV. Conclusions

The model presented in this paper can be used as a tool for long-term energy supply planning. By incorporating multiple energy carriers as possible portfolio outputs, energy generation planning is addressed in an integrated way. Moreover, the combination of mean-variance portfolio theory and multi-criteria analysis enables the assessment of portfolio performance and incertitude in a comprehensive manner. Using this method, an efficient energy technology mix for the generation of multiple energy carriers can be determined. Such an efficient technology portfolio minimizes the exposure to the full spectrum of incertitude. Furthermore, the possibility of including multiple performance criteria allows for the identification of portfolios that satisfy the triple bottom line of sustainability comprising economic, environmental and social criteria.

Future work will be related to determining optimal transition strategies for a dynamic evolution from today's portfolios to portfolios that optimally meet the criteria and requirements of the future.

Appendix A
MVP cost data

Table II provides the levelized energy generation cost data for all technologies in each scenario used in the MVP part of the analysis. Data from reference [10] served as basis for the scenario building, which was done through variation of the different states of external factors.

Appendix B
MDA performance and disparity data

Tables III and IV present the normalized values of the performance indicators and disparity attributes used for the

TABLE II
LEVELIZED ENERGY GENERATION COSTS FOR ALL TECHNOLOGIES IN ALL SCENARIOS IN [USD/MWH].

	S1	S2	S3	S4	S5	S6	S7	S8
T1	43.3	43.3	44.2	44.2	43.3	43.3	44.2	44.2
T2	39.7	39.7	40.5	40.5	39.7	39.7	40.5	40.5
T3	253.3	253.3	287.8	287.8	253.3	253.3	287.8	287.8
T4	86.8	67.5	74.5	96.4	70.7	51.4	58.4	80.3
T5	59.9	59.9	63.0	63.0	59.9	59.9	63.0	63.0
T6	81.4	64.7	66.0	83.0	77.8	61.2	62.4	79.4
T7	13.2	13.2	14.7	14.7	13.2	13.2	14.7	14.7
T8	16.8	13.9	14.0	17.0	10.4	7.5	7.6	10.6

MDA part of the analysis. If available for the considered technologies, performance and disparity data from Annex B of reference [11] was taken. For the other technologies, own estimates were made.

TABLE III
TECHNOLOGY PERFORMANCE VALUES.

	Cost performance	Environmental performance	Public acceptance	Long-term security	System operation
Weight	0.30	0.25	0.15	0.20	0.10
T1	0.70	0.80	0.60	0.90	0.30
T2	0.70	0.80	0.60	0.80	0.90
T3	0.10	0.90	0.60	0.90	0.40
T4	0.10	0.65	0.50	0.50	0.90
T5	0.70	0.80	0.60	0.70	0.60
T6	0.70	0.65	1.00	0.50	0.90
T7	0.80	0.90	0.60	0.90	0.50
T8	0.60	0.50	0.90	0.50	0.80

TABLE IV
TECHNOLOGY DISPARITY VALUES.

	Fossil fuel	Building integr.	CHP generation	Output controllability	CO_2 regulation	Level of maturity
Weight	0.2	0.2	0.2	0.2	0.1	0.1
T1	0.0	0.0	0.0	0.2	0.0	0.5
T2	0.0	0.0	0.0	0.5	0.0	0.0
T3	0.0	1.0	0.0	0.1	0.0	1.0
T4	1.0	1.0	1.0	1.0	1.0	1.0
T5	0.0	1.0	1.0	0.8	1.0	0.5
T6	1.0	1.0	1.0	1.0	1.0	0.0
T7	0.0	1.0	0.0	0.2	0.0	0.5
T8	1.0	1.0	0.0	1.0	1.0	0.0

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