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Combining scenario planning, energy system analysis, and multi-criteria analysis to develop and evaluate energy scenarios

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ABSTRACT

The transition from the current electricity system to a renewable electricity supply poses immense economic, technological, and policy challenges. Energy system models represent the complexity of interactions in combined processes from extraction of primary energy to the use of the final energy to supply services and goods. While these models were originally focused on energy security and costs, climate change, as the most pressing environmental concern as well as sustainability in general require the consideration of a broader range of decision-relevant aspects. In this context, scenario planning and multi-criteria decision-making can complement energy system analysis in the development and evaluation of energy scenarios. Therefore, we propose a combination of these three methods and illustrate it in a case study that investigates the transition of the electricity sector in Lower Saxony, Germany, to energy from renewable sources. The results of our case study show that the integration of multi-criteria analysis allows for better Problem structuring by focusing on relevant alternatives, external uncertainties, and evaluation criteria. The integration of scenario planning allows for a systematic investigation of external uncertainties. Thereby, the fallacy of investigating particular assumptions for uncertain parameters, which are however not consistent with the assumptions in the scenario, can be avoided. Finally, combining the methods allows for a more balanced and objective evaluation of alternative energy systems in terms of multiple criteria, which can be used to inform discussions among stakeholders and may thus increase acceptance.

1. Introduction

The major objective of energy policy in the European Union is to ensure a competitive, sustainable, and secure energy supply (European Union, 2010). To achieve this energy policy triangle, the *energy transition* – shifting the current fossil and nuclear-based energy supply and related planning and operation processes to energy from renewable sources – plays a key role. The EU has the long-term goal of reducing greenhouse gas emissions by 80–95% until 2050, compared to 1990 levels. To analyze whether this long-term goal can be reached, *energy scenarios* are developed and used (Cao et al., 2016; Dieckhoff et al., 2014). Energy scenarios describe *possible* representations or developments of the future energy system in terms of technical and organizational options (Grunwald et al., 2016). They are usually quantitatively underpinned by energy system models stemming from *energy system analysis* (ESA). These models are abstract, simplified representations of real (or future) energy systems for analyzing supply and demand of energy (Möst and Fichtner, 2009). Initially, energy system models were focused on energy security and costs, but today, they also focus on pathways to achieve significant reductions in greenhouse gas emissions needed to limit climate change (Pfenninger et al., 2014). However, economic competitiveness, sustainability, and supply security are usually conflicting, measured with incommensurable units, and may be weighed differently by different stakeholders. Therefore, identifying the best transition pathway towards a renewable energy supply is hard and calls for integration of a Problem structuring method (Antunes and Henriques, 2016; Hake et al., 1994).

Given this complex background, a suitable approach for a systematic and transparent evaluation of energy scenarios is needed. Methods from multi-criteria analysis (MCA) may be suitable for such evaluations because stakeholders' preferences can be taken into account (Greco et al., 2016). To make decision support and recommendations drawn from energy scenarios more transparent,

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scenario planning (SP), ESA, and MCA could be combined. Combining these three methods is challenging, mainly because the term *scenario* is used ambiguously in the literature (Stewart et al., 2013; Marttunen et al., 2017). While Stewart et al. (2013) offer some generic guidelines for integrating SP and MCA, we investigate a more detailed process model in the context of energy scenarios. We apply it in a case study to evaluate different transition pathways of the power generation system in Lower Saxony, Germany, to a higher share of energy from renewable sources. This case study both illustrates how the framework can be used and provides a basis for evaluating the framework.

This paper is organized as follows. In Section 2, we provide a brief overview of the processes of SP, ESA, and MCA. In Section 3, we describe the framework of combining SP, ESA and MCA, before we provide in Section 4 an illustrative application of the framework to a case study of an energy transition planning process. In Section 5, we discuss benefits, challenges, and limitations of our framework that could be observed in the case study. Finally, we summarize the main findings.

2. Theoretical background

Although scenario planning is experiencing a rising popularity ever since the oil crises in the 1970s, the use of the term scenario is ambiguous, because different scenario concepts relate differently to uncertainty. A definition of uncertainty that also includes the notion of a system that is to be modeled is given by Zimmermann (2000, p. 192): "*Uncertainty* implies that in a certain situation a person does not possess information which quantitatively and qualitatively is appropriate to describe, prescribe, or predict deterministically and numerically a system, its behavior, or other characteristics."

While there also exist different categorizations of uncertainty (e.g. (French, 1995; Zimmermann, 2000),), the distinction between internal and external uncertainty is of utmost importance for energy scenarios (Stewart and Durbach, 2016; van der Pas et al., 2010). *Internal uncertainty* relates to the process of Problem structuring and analysis. This includes uncertainty about the appropriateness of a developed system model for a particular real-world problem (Grunwald et al., 2016), or uncertainty about the judgmental inputs required from analysts or stakeholders (Stewart and Durbach, 2016). *External uncertainties* are not influenceable by stakeholders and relate to the nature of the environment and its influence on the *performance scores*, e.g., levelized costs of electricity or CO_2-emissions, of a particular alternative (Stewart and Durbach, 2016). In energy scenarios, an *alternative* is usually a combination of technical and organizational options, e.g., a decentralized energy supply based on distributed renewable resources or a centralized energy supply based on large-scale renewable and conventional power plants, while typical external uncertainties include the development of the price of crude oil or the economic growth rate (Dieckhoff et al., 2014). Scenario planning can be used to define a combination of different uncertain parameters in a systematic way. Thereby, the combined assumptions should be internally consistent.

According to Grunwald (2011), the life cycle of energy scenarios can be divided sequentially into construction, evaluation, and impact. In the construction phase, SP and ESA can complement each other in the so-called "Story-and-Simulation" approach (Alcamo, 2008; Weimer-Jehle et al., 2016). SP can be used to devise qualitative context scenarios, which are then translated into quantitative assumptions in the ESA. In the subsequent evaluation phase, MCA can be applied to evaluate the quantitative results of ESA. Following this sequential order, we describe the processes used in SP, ESA, and MCA in the following subsections. In particular, we examine how each method addresses external uncertainties and how stakeholders can be involved. Thereafter, we describe the rationale, challenges, and the purpose of combining SP, ESA, and MCA in detail.

2.1. Process of scenario planning

Scenario planning (SP) is a method for imagining possible futures that was first developed for military purposes by Kahn and Wiener (1967) and was later applied to situations of decision making under uncertainty in different fields, including business administration, politics, and environmental management (Schoemaker, 1995). The objective of SP is "to provide a structured 'conversation' to sensitize decision makers to external and uncontrollable uncertainties and to develop a shared understanding of such uncertainties" (Stewart and Durbach, 2016, p. 486). SP significantly differs from sensitivity analysis, which assesses the relative impact of certain variables on the results of a model (Schoemaker, 1995; Gal et al., 1999; Saltelli, 2007). In contrast, SP defines a consistent set of parameters, which forms a scenario.

Gausemeier et al. (1998) designed a practical approach for SP for the application in the management of businesses and structured it into five steps, to be carried out by neutral analysts, the so-called scenario team.

(1) Scenario-Preparation: The objective of the SP process is defined first. The so-called decision field can be influenced by the stakeholders. In the energy sector, this can correspond to a power system of a state, which can be broken down into several decision field elements, such as the capacities of various electricity production technologies and storage systems.
(2) Scenario-Field-Analysis: Next, a scenario field is defined, which may include different external uncertainties that cannot be influenced by the stakeholders. The key factors driving the future development of the scenario field need to be identified and operationalized. Three types of scenarios can be distinguished (see Fig. 1).

Internal scenarios comprise only key factors from the decision field and thus can be influenced. In energy scenarios, internal scenarios can be alternative power system configurations, such as decentral or central (see, e.g., Madlener et al., 2007; Browne et al. (2010); Diakoulaki and Karangelis (2007); Jovanović et al. (2009); Kowalski et al. (2009); Trutnevyte et al. (2011)).

External scenarios comprise only key factors from outside of the decision field and thus cannot be influenced. For example, in a power system, power supply and demand always need to be balanced. The surplus power produced by neighboring states, which can be imported in times of production shortages, cannot be influenced by the investigated state and is therefore part of an external scenario. For further examples of external scenarios, see Comes et al. (2013), Durbach and Stewart (2012), Goodwin and Wright (2001), Marttunen et al. (2017), Montibeller et al. (2006), Stewart et al. (2013), Stewart and Durbach (2016), and van der Pas et al. (2010).

System scenarios comprise key factors from both inside and outside of the decision field and thus can only be partly influenced by the stakeholders. They distinguish the uncertainties attached to each scenario and thereby limit the future space for the decision field. If internal and external scenarios are developed as system scenarios in one common SP process, the consistency of their assumptions is checked.

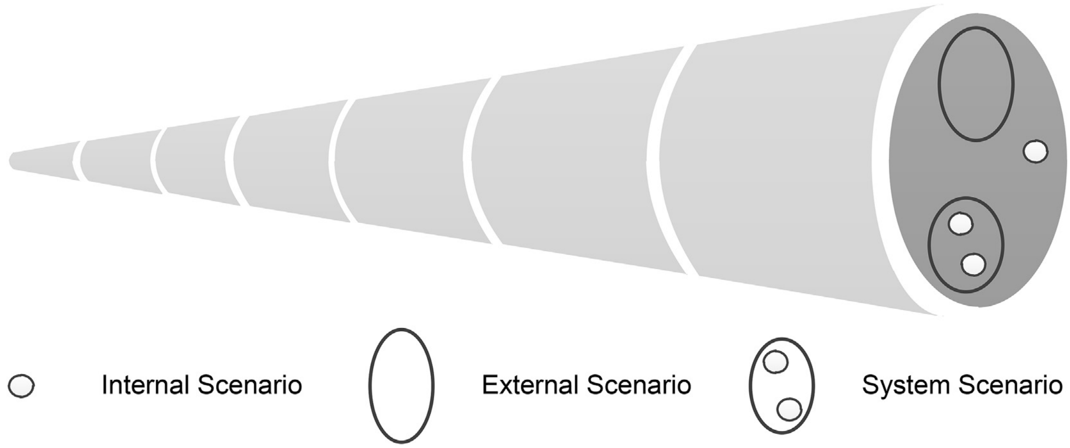

Fig. 1. Scenario classification.

(3) Scenario-Prognostic: In this step, possible developments (usually up to four) for each selected key factor, so-called projections are described. SP aims at challenging the prevailing mind-set, because the objective is not to find the most likely projection but to think of extreme developments. To that end, the projections should cover a broad range of possible future developments.
(4) Scenario-Development: With a pair-wise comparison of projections, a consistency matrix is created. A *k*-means cluster analysis (MacQueen, 1967) can be used to build *k* clusters, based on the consistency of all projections. The clusters represent the scenarios that are internally consistent, but different among themselves. To make the scenarios more tangible, textual descriptions are formulated.
(5) Scenario-Transfer: The effects of scenarios on the decision field are analyzed. Gausemeier et al. (1998) propose a qualitative assessment of strengths, weaknesses, opportunities, and threats (SWOT-analysis). According to stakeholders' attitudes toward risk, they can use the results of this analysis to develop strategies for the decision field.

Although the approach developed by Gausemeier et al. (1998) is designed foremost for developing business strategies, it can be adopted for the development of energy scenarios, as will be further elaborated in Section 3. Energy system analysis can complement the qualitative storylines from scenario planning with quantitative data.

2.2. Process of energy system analysis

Energy system analysis (ESA) comprises various methods that help to enhance the understanding of the operating principles of the energy system and its components. The objective of ESA is to support decisions in energy policy and energy research with regard to technologies and infrastructures for the energy supply and energy conversion in a scientific and systematic way (Cao et al., 2016; Möst and Fichtner, 2009; Witt et al., 2018).

Originally, large bottom-up *optimization* models have been designed to minimize total energy system costs (Pfenninger et al., 2014). This way, these models aim to find an optimal solution, i.e., the single best alternative, in a given external scenario, which is modeled as constraints within for example linear, non-linear, and mixed-integer linear models. To find different alternatives in a given external scenario with an optimization model, one can minimize or maximize different objective values, e.g., minimizing CO_2-emissions or net energy imports (McKenna et al. (2018)).

Energy system *simulation* models focus on predicting the system's likely evolution. In contrast to the often rigid mathematical formulation of optimization models, such simulation models can be built modularly and incorporate a range of methods (Pfenninger et al., 2014). Their higher flexibility allows the investigation of more alternatives in given external scenarios (Lund et al., 2017).

There are some generalized descriptions of the process of (energy) system analysis (Hake et al., 1994; Küll and Stähly, 1999; Möst and Fichtner, 2009; Schönfelder et al., 2011). Based on these, the process of ESA can be divided into the following steps.

(1) Problem formulation: The modeling process is initiated when a problem is identified and formulated. The stakeholders of the problem are identified, and both purpose and objective of the modeling process are defined with respect to stakeholders' views.
(2) Modeling (Data collection, model development, model implementation, and model validation): The input data required for quantifying the model parameters are collected, and the model is developed and implemented. *Model development* means developing a formal representation (e.g., an optimization or simulation model) of the system, which is followed by its *implementation* in a programming language or using software tools. The next step is *validation*, which means verifying that the model correctly represents the defined system within the system boundaries. For example, the model can be tested using historical real-world data, a process known as back testing (Möst and Fichtner, 2009). If a model does not satisfy the requirements, it may need to be adapted or supplemented with additional data, which can lead to multiple iterations within this step.
(3) Model application: To explore different solutions of the Problem and gain insights, different parameter combinations are defined, for instance different electricity generation costs. Such a parameter combination represents an external scenario. The current literature on ESA does not explicitly describe how to define external scenarios. Depending on the problem, it can be useful to investigate the impact of additional restrictions or different objective functions in an optimization model. In the case of simulation models, different alternatives need to be defined, for example, combinations of renewable energy technologies resulting in a particular energy mix. The simulation model can then be used to investigate the performance scores of these

alternatives in each external scenario. Sensitivity analysis can be used to explore the effect of particularly uncertain or important parameters.

(4) Analysis and interpretation of the model results: After calculating the results for the defined external scenarios, their plausibility needs to be checked. For example, a violation of the laws of physics is an indication for an error in the model and calls for correction, so that the previous steps may need to be iterated.

(5) Transfer to the real system: Finally, the results are transferred to the real system. In this step, different questions need to be answered, including: Do the model results address the Problem identified in the problem formulation? Can robust solutions be found when parameters are varied? Can these solutions provide adequate decision support for the real problem? Which conclusions can be drawn for the real system? If the model results cannot answer these questions in a satisfactory way, the process may need to be iterated.

2.3P. rocess of multi-criteria analysis

Multi-criteria analysis (MCA) is a formal approach to solving problems with several conflicting criteria (Greco et al., 2016; French and Geldermann, 2005; van der Pas et al., 2010). The methods explicitly acknowledge subjectivity in decision making, provide a framework for sensitivity analysis, and offer support for building consensus in group decision making (McKenna et al., 2018). In the energy sector, MCA has been applied to such planning problems as comparing power generation technologies, selecting energy projects, and guiding the formulation of energy plans and policies (Antunes and Henriques, 2016; Oberschmidt et al., 2010; Spronk et al., 2016; Steinhilber et al., 2016). Basically, various discrete alternatives are assessed against several criteria, taking preferences of the decision makers into account. MCA can be structured into three high-level steps with an iterative character and a fluid transition between them (Belton and Stewart, 2003; French and Geldermann, 2005).

(1) Formulate Problem: Various problem structuring methods (PSM) facilitate effective structuring of a problem situation rather than “solving” it directly by applying the actual MCA algorithm (Marttunen et al., 2017; Rosenhead, 1989). Belton and Stewart (2003) propose the CAUSE checklist (Criteria, Alternatives, (external) Uncertainties, Stakeholders, Environment) for collaboration with the stakeholders, to ensure that key components of a decision problem are not overlooked.

Several technical, economic, environmental, and social *criteria* are used for evaluating the competitiveness, sustainability, and supply security of energy systems (Antunes and Henriques, 2016). The criteria should be measurable, relevant, understandable, and non-redundant. They can be ordered into a criteria hierarchy where a higher-level objective is sub-divided into multiple criteria that can be operationalized.

Deriving *alternatives* to solve the Problem at hand (i.e., performing well in achieving the conflicting criteria) can be supported by “value focused thinking” (Keeney, 1992; Siebert and Keeney, 2015). Alternatives can also be generated with a morphological box by re-combining characteristics of existing alternatives (Zwicky, 1967). In the case of energy scenarios, an alternative is usually a combination of technical and organizational options, e.g., a decentralized energy supply based on distributed renewable resources or a centralized energy supply based on large-scale renewable and conventional power plants.

A key question in MCA concerns, which *uncertainties* are critical for the assessment of alternatives and how the consideration of these will be incorporated in the analysis. Especially in long-term decision-making, such as energy system planning, it is necessary to accept uncertainty and acknowledge the need to address this through qualitative analyses. In that context, SP would be a suitable supplement to MCA.

Next, the relevant *stakeholders* in the decision Problem should be identified, which can be assisted by stakeholder analysis (Grimble and Wellard, 1997). For energy system planning on a local level, all decision makers and relevant stakeholders can usually be identified and involved in the actual decision process (Lerche et al., 2017; McKenna et al., 2018). For decision problems with greater geographical scope or covering several decades, this is more complicated or may become infeasible (Steinhilber et al., 2016).

The *environment* of the decision Problem includes all factors that may have an influence on the decision but are not relevant or interesting enough to be modeled as an external scenario (Stewart et al., 2013).

(2) Evaluate options: Once the decision Problem has been well defined, a *decision table* can be conceived, which comprises for each considered alternative the respective performance scores for each criterion. A multitude of computations to support consequence modelling, statistical analysis, and decision analysis might be necessary to derive those performance scores, such as CO_2-emissions of the different alternatives. In this context, it is important to separate the science, predictions of what might happen as a result of possible actions, from the value judgements of how much each possible consequence matters (French and Geldermann, 2005). *Weighting factors* indicate the importance of each criterion within the overall decision. Different weighting methods exist, of which some require the input of stakeholders and others do not (Wang et al., 2009).

Numerous *MCA algorithms* have been proposed to aggregate the decision matrix with stakeholders' preferences (Greco et al., 2016), including multi-attribute utility theory (MAUT), analytical hierarchy process (AHP), and preference ranking organization method for enrichment evaluations (PROMETHEE). The robustness of the obtained results by those algorithms or the influence of the chosen weighting factors is usually investigated by sensitivity analysis.

(3) Review the decision structure: The process is complete when the decision makers are comfortable with the results. Otherwise, the Problem may need to be re-structured and the process iterated, by refining the used models, analysis of further data, or applying forecasting techniques.

2.4. Benefits and challenges of combining scenario planning, energy system analysis, and multi-criteria-analysis

Following the short characterization of SP, ESA, and MCA in the previous sections, their integration for the development and evaluation of energy scenarios is proposed. Table 1 shows, where an integration of the methods can provide added value. The rows indicate, from which method the benefits originate, while the benefitted methods are shown in the columns. For example, SP can support ESA in the *(3) model application* step by helping to develop consistent external scenarios and alternatives, which can for example serve as input for a simulation model.

When combining the three methods, the following must be

Table 1
The benefits of combining Scenario Planning (SP), Energy System Analysis (ESA), and Multi-Criteria Analysis (MCA).

	SP	ESA	MCA
SP	–	(3) Model application: • Develop external scenarios • Create alternatives for simulation models	(1) Formulate Problem: • Create alternatives • Develop external scenarios (2) Evaluate options: • Examine robustness of alternatives (Marttunen et al., 2017) • Identify higher-order interactions with internally consistent scenarios (Dieckhoff et al., 2014; Stewart and Durbach, 2016; Weimer-Jehle et al., 2016)
ESA	(5) Scenario-Transfer: • Quantify the effects of external scenarios on decision field (Weimer-Jehle et al., 2016) • Investigate impact of particularly uncertain parameters on model results, e.g., via sensitivity analysis	–	(2) Evaluate options: • Provide system model for calculating performance scores • Investigate impact of uncertainties on model results, e.g., via sensitivity analysis
MCA	(2) Scenario-field-analysis: • Identify relevant uncertainties (5) Scenario-Transfer: • Evaluate the consequences of external scenarios on the decision field (alternatives) in a transparent and systematic way (Durbach and Stewart, 2003) • Aggregate multi-dimensional data, which may reduce information overload and complexity of scenarios for stakeholders (Kowalski et al., 2009)	(1) Problem formulation: • Structure decision Problem by helping to identify relevant evaluation criteria *(3) Model application:* • Create alternatives for simulation models (4) Analysis and interpretation of the model results: • Evaluate alternatives/solutions with multiple, conflicting criteria in different external scenarios • Evaluate impact of different assumptions (e.g., regarding criteria weights) with sensitivity analysis • Reduce information overload and complexity of model results for stakeholders (5) Transfer to the real system: • Account for different stakeholders' preferences in a transparent way, increase acceptance of evaluation, and build consensus among stakeholders (Antunes and Henriques, 2016)	–

considered: First, the ambiguous use of the term scenario in the literature (internal scenario vs. external scenario). If only internal scenarios comprising the decision field are developed, this implies that effects of external uncertainties are not investigated, which is inadequate for the long time horizons of energy scenarios. Second, calculating performance scores of several alternatives in different external scenarios with the help of complex system models may be time-consuming. Third, the interpretation and elicitation of stakeholders' weights may be challenging, if different weights are set for different scenarios (Karvetski et al., 2011; Oberschmidt et al., 2010). Finally, a major challenge that arises for evaluating energy scenarios is their broad scope, concerning regional, national or international system boundaries, techno-economic parameters of the existing and emerging technologies, as well as stakeholders. A decision maker (or group thereof) cannot be clearly identified, because there simply are too many actors that have different authorities over necessary resources (including energy suppliers, transmission system operators, non-energy companies, the general public, government institutions, and non-government organizations) (Steinhilber et al., 2016). During the process, it may be necessary to anticipate the views of non-participating relevant stakeholders for taking them into consideration.

3. Framework for integrating scenario planning, energy system analysis, and multi-criteria analysis

The combination of SP, ESA, and MCA can provide a structured method for developing long-term scenarios and comparing them with regard to multiple criteria. The proposed combination of the three methods is suggested as follows: First, with *SP*, alternatives and external scenarios are defined; second, with *ESA*, the performance scores of alternatives in different scenarios are determined; and third, in *MCA*, preferences and performance scores are aggregated. This methodological framework for long-term decision problems in the energy sector is designed for the cooperation between a scenario team and analysts for energy system modeling and MCA. The decision context is characterized by deep uncertainty (Walker et al., 2003), which means that stakeholders, analysts, and experts do not know or cannot agree on the system model, the probability distributions for inputs to the system model, and/or the preference model (van der Pas et al., 2010). For example, there is no consensus among experts on how prices for crude oil or CO_2-certificates will develop or what the energy market design of the future is.

Two prototype process models for the framework have been presented in Schwarz et al. (2017) and Schwarz et al. (2018) but are not yet explicitly linked to the processes of SP, ESA, and MCA. Fig. 2 shows the framework, where the individual methods are highlighted by different shapes and dashed black edges. Steps present in multiple methods are marked accordingly. The process is iterative.

In the *Problem formulatio*n, the problem is structured. In particular, the overall objective of the decision support process is identified, which also determines the system boundary. Although an energy system model can be built without identifying stakeholders, they are indispensable for the decision support process and should be identified.

The *data collection* of ESA is enriched by SP, which is used to develop alternatives as well as external scenarios. *Systems scenarios* should be defined first, according to the SP process proposed by Gausemeier et al. (1998). For the *definition of system scenarios,* qualitative stories about conceivable future conditions are developed. Ideally, stakeholders are included in this step to provide their expertise and preferences, e.g., through participatory workshops. To transform qualitative stories to quantitative assumptions, our

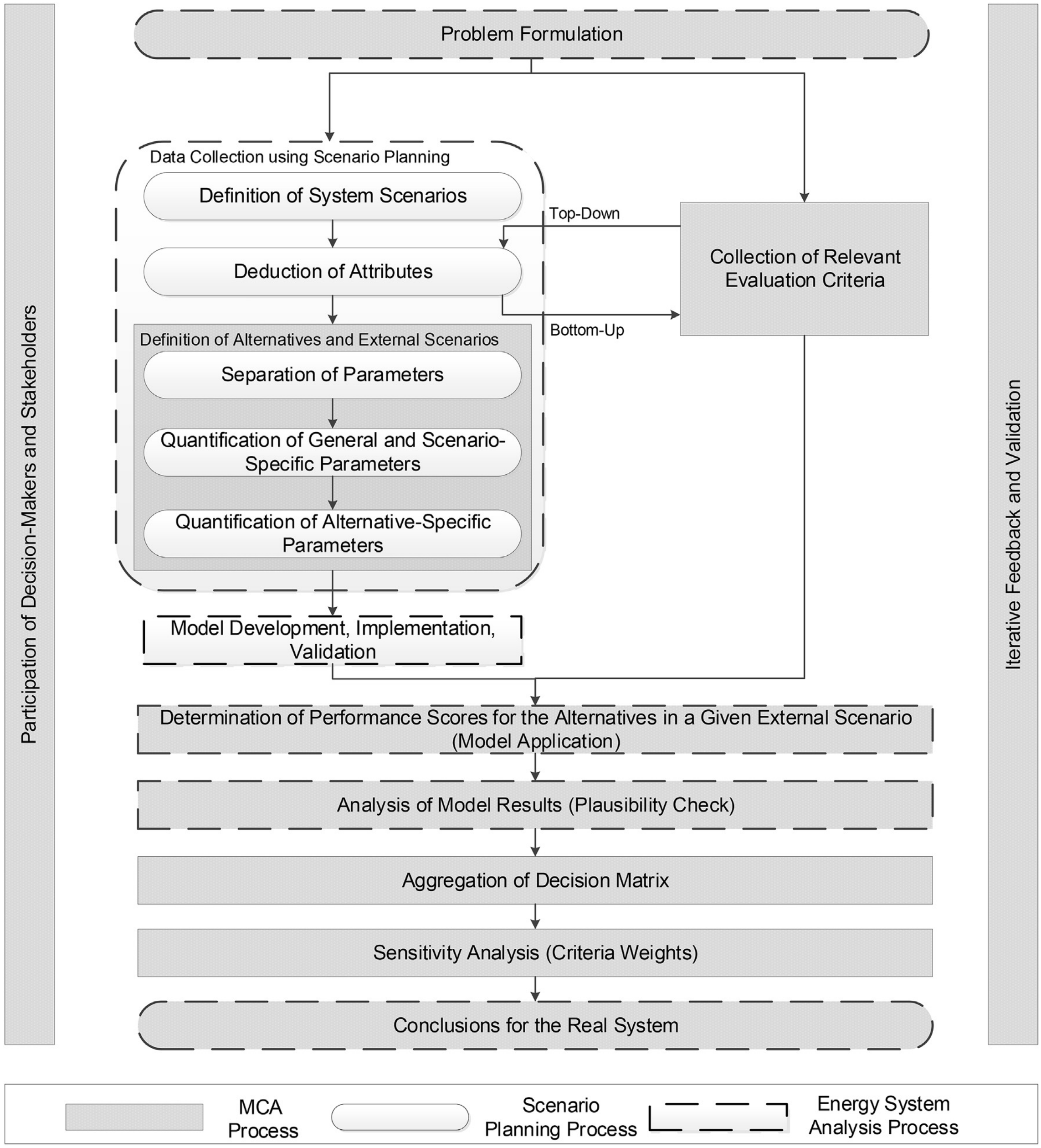

Fig. 2. Framework for developing and evaluating energy scenarios as a combination of Scenario Planning, Energy System Analysis, and Multi-criteria Analysis.

framework follows the story-and-simulation approach defined by Alcamo (2008).

The *deduction of attributes* yields system attributes, that is, parameters and endogenous variables. Parameters are used as input for models, while endogenous variables are results of model calculations.

The *collection of relevant evaluation criteria* is driven mainly by the *problem formulation*. Thus, the highest level of the criteria hierarchy represents the major objective, for example, identifying a sustainable energy system by 2050 for Lower Saxony.

In the *separation of parameters,* general, scenario-specific, and alternative-specific parameters are differentiated, depending on the specific decision Problem, its objective, and the associated stakeholders: *General parameters* apply to all scenarios, e.g., general socio-economic parameters. Parameters included in an external scenario are *scenario-specific* and can vary from scenario to scenario, e.g., prices for crude oil and natural gas, the economic growth rate, and the diffusion of smart meters into private households and industry. Parameters included in an alternative are *alternative-specific* and can vary from alternative to alternative, e.g., the share of households participating in a smart grid.

The *quantification of general and scenario-specific parameters* can be based on related literature, measured values, model calculations, or ad hoc assumptions (Grunwald, 2011). In addition, possible ranges for the alternative-specific parameters need to be defined for each scenario to reflect that system scenarios limit the scope of alternative-specific parameters.

Based on these ranges, consistent sets of parameter values need to be defined for each alternative in the *quantification of alternative-specific parameters.*

The model *development, implementation and validation* are the same in our approach as in ESA (see Section 2.2). Because

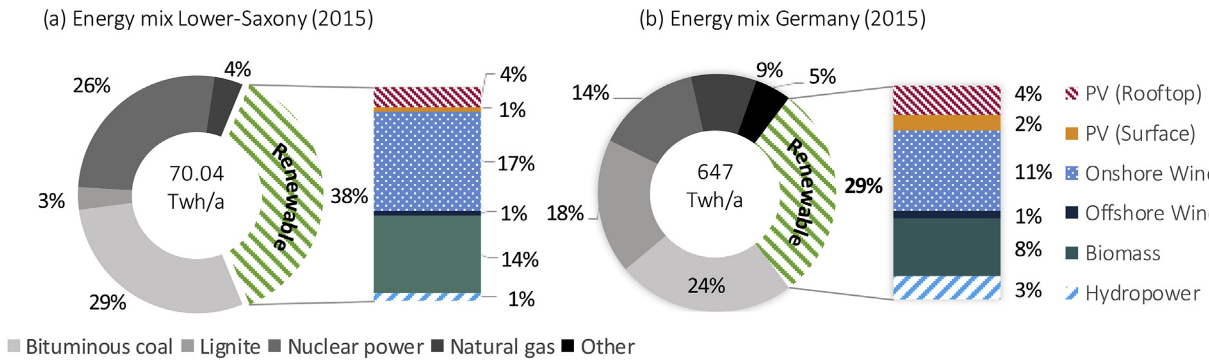

Fig. 3. Energy mix of Lower Saxony (a) and Germany (b) for the year 2015 (Bundesnetzagentur, 2015; Bundesnetzagentur, 2016).

alternatives and external scenarios have already been defined in the previous steps, the implemented energy system model can be parametrized accordingly to *determine performance scores for the alternatives in a given external scenario*.

The *aggregation of the decision matrix* also encompasses the stakeholders' preferences by means of an MCA method (see Section 2.3). A *sensitivity analysis* should be performed for the criteria weights. Finally, *conclusions for the real system* can be drawn from the developed energy scenarios. The results of the process should be made publicly available, along with a clear description of the process that led to them.

4. Case study: evaluation of future power generation systems in Lower Saxony

In this case study, the framework of combining SP, ESA, and MCA is applied to a decision Problem concerning the transition of the electricity sector in the state of Lower Saxony, Germany, from a mainly conventional (fossil and nuclear) energy supply to energy from renewable sources. This decision problem is addressed in the research project NEDS (*Sustainable Energy Supply Lower Saxony*).[1] Different members of the interdisciplinary project team took different roles of analysts, i.e., the scenario team from SP and the analysts from ESA and MCA.

Especially, the de-carbonization of the electricity sector is considered crucial, because the generated electricity is projected to be required in other energy sectors in the future, e.g., for heat pumps in the heat sector or for electric vehicles in the transport sector (Sternberg and Bardow, 2015). National targets for the power sector are defined by the German Renewable Energy Sources Act (EEG) and require that, by 2050, at least 80% of electricity production should come from renewable sources (The Federal Government, 2016). In 2015, renewables accounted for 29% of power production in Germany. Fig. 3 shows that most of the renewable energy came from onshore wind and biomass. Lower Saxony, which produces approximately 9% of the national electricity, has a share of 38% renewable electricity. The state has the second largest area of all states in Germany. Due to a comparably low number of inhabitants, it has the fifth-lowest population density of all sixteen German states (Statistisches Bundesamt, 2018a). In Lower Saxony, the shares of onshore wind and biomass of the total power generation are higher than the national average, while photovoltaic power generation is similar.

Although, unlike the Federal Government, the states have direct legislative power in only a few areas of climate protection, they have sufficient options to influence the transition to a renewable electricity system and its layout through administrative action, e.g., by awarding financial subsidies and through land use planning. Therefore, it is also important to plan this transition on a state level. Regarding Lower Saxony, Faulstich et al. (2016) describe possible target states for the energy system of the state in 2050. The aim of the mentioned research project NEDS is the development and evaluation of promising transition paths. Additionally, any interested stakeholders should be involved to increase the acceptance of the developed alternatives, scenarios, evaluation criteria, and subsequent evaluation results. In the following, the application of each step of the framework (see Fig. 2) is presented.

Problem formulation: The problem is to identify future system configurations of the power generation system (alternatives) for a competitive, sustainable, and secure energy supply in Lower Saxony. Specifically, the power generation system should gradually move toward higher shares of renewable energy until 2050, when 80% renewables should be reached, following the national target. The alternatives should therefore feature high shares of power from renewable sources, but may differ, e.g., in capacities of energy storage systems. The effects of external uncertainties, e.g., general economic conditions, on the performance scores of the alternatives are to be investigated. The evaluation criteria, the alternatives, and uncertainties are to be refined through stakeholder participation. In this case, it is not possible to clearly identify a decision maker, since no single person or group can stipulate how the future energy system of Lower Saxony will be designed in 2050. However, it is possible to identify various stakeholders for the decision process, including the general public, prosumers, politicians, and energy suppliers. In the Problem formulation, there was only indirect stakeholder involvement, but the problem was defined with current political and societal concerns in mind.

Define system scenarios: To develop system scenarios for the power system of Lower Saxony, an expert-guided workshop was conducted following the steps of the SP process as described in Section 2.1. The Scenario-Field-Analysis resulted in 11 key factors that have a major influence on the development of the power system. Each key factor is modeled with two dimensions:

1. Topology of power plants: This key factor represents the spatial distribution and size of power plants, with the dimensions *plant size (small/big)* and *distance to consumers (near/far)*.
2. Energy mix represents the shares of renewable and fossil energies in the net electricity generation, with the dimensions *share of renewable energies (low/high)* and *share of fossil energies (low/high)*.

[1] In German: Nachhaltige Energieversorgung Niedersachsen. For more information on the project, see Blaufuß et al. (2019).

3. Levelized cost of electricity represents the future development of the levelized costs of electricity for both renewable and fossil energies. The two dimensions are *levelized costs of electricity of fossil-fueled power plants (decrease/increase)* and *levelized costs of electricity of renewable energy technologies (decrease/increase).*
4. Power grid describes the nature of the power grid, with the dimensions *expansion of power lines (low/high)* and *use of controllable equipment (low/high).*
5. Digitalization in the distribution grid depicts the level of digitalization in the distribution grid, with the dimensions *market penetration of intelligent electric devices (low/high)* and *diffusion of ICT-infrastructure in the distribution grid (low/high).*
6. Energy management describes the diffusion of energy management systems in private households and industry with the dimensions *application in private households (low/high)* and *application in industry (low/high).*
7. Energy demand (private households) is dependent on the consumer behavior and number of electric devices *per capita*. The two dimensions are *diffusion of resource-saving behavior (low/high)* and *number of electric devices per capita (low/high).*
8. Economy and its energy demand describes the energy intensity and growth of the economy, with the dimensions *economic growth rate (low/high)* and *energy intensity (low/high).*
9. Energy policy and international coordination reflects national and international developments in energy policy. The two dimensions are *market regulation (create markets/strong regulation)* and *international coordination of the energy transition (low/high).*
10. Knowledge and perceived control describes the knowledge of individuals about and perceived opportunities to control renewable energy technologies in the smart home or smart grid. The two dimensions are *knowledge about the environment (low/high)* and *perceived control (low/high).*
11. Acceptance: This key factor describes the acceptance of renewable energy technologies on both individual and societal levels as a function of cost-benefit ratios. The two dimensions are *individual cost-benefit ratio (low/high)* and *societal cost-benefit ratio (low/high).*

For each key factor, four projections were developed in the Scenario-Prognostic, resulting in 44 projections. In the *Scenario-Development*, the project team evaluated the pair-wise consistency of projections, resulting in a consistency matrix. A subsequent cluster analysis of this matrix yielded five consistent system scenarios (see Table 2).

We presented these five scenarios (S1—S5) at a public symposium, to which the interested public and researchers in the field of energy transition in Lower Saxony were invited. The feedback on and discussion of the five scenarios by the approximately 50 participants was rather limited, however, which may be attributed to the scenarios' complexity, and therefore, they were not further refined.

Deduction of attributes: In this step, the project team developed about 230 attributes to quantitatively model the development of each key factor of the system scenarios in more detail. Three examples are crude oil prices, population development, and installed capacity. To support the deduction of attributes, an information model was used to map the relationships between attributes, energy system models, and criteria, and generate an ontology-based database schema from it (Schwarz et al., 2018). The deduction of attributes was largely supported by a broad literature research, and the project team was able to develop a sufficient number of attributes in this step.

Collection of relevant evaluation criteria: First, the project team collected, condensed, and arranged a set of potentially relevant evaluation criteria from the literature in a hierarchy. Second, a survey with 29 participants was conducted at a second public symposium, to which, again, the interested public and researchers in the field of energy transition in Lower Saxony were invited. Half of these participants stemming from science and research while 38% can be characterized as "economy, business, and interested citizens". From these 29 participants, 10 particularly interested citizens between 27 and 75 years participated in semi-structured interviews. Members of the project team applied a qualitative content analysis to both the surveys and interviews to identify relevant criteria (Blaufuβ et al., 2019). The final criteria catalogue is a synthesis from the literature review and the results of the qualitative content analysis. Table 3 depicts the criteria hierarchy derived for the evaluation of energy scenarios for Lower Saxony until 2050. The major objective is split into four sub-objectives, which are further broken down into one or more measurable criteria. The criteria are grouped into sub-objectives according to the results of the qualitative content analysis.

Separation of parameters: Since the state government of Lower Saxony can influence the expansion of the power generation system in the long term, we classified the capacity expansion as an *alternative-specific parameter.* Two other alternative-specific parameters are the number and capacities of energy storage systems at different voltage levels of the power grid and the share of private households whose power supply and demand can be coordinated locally in a smart grid.

Quantification of general and scenario-specific parameters: To define the parameters, calculations were based on related studies or on own assumptions. Table 4 contains some examples of parameter values for the year 2050. Note that scenario-specific and general parameters are quantified with discrete values, whereas alternative-specific parameters are quantified as intervals.

The consistency analysis from SP (Gausemeier et al., 1998) can help to *define alternatives* in a structured way. This method was also used to define the system scenarios. Here, however, the *alternative-specific parameters* (see top part in Table 4) are considered as *key factors*, so that projections are defined for those. Based on evaluating the pair-wise consistency of projections, we performed a cluster analysis, yielding the following alternatives:

- decentralized energy system (A1),
- centralized energy system (A2),
- and a mix of both (A3).

The previously defined intervals are used in the *quantification of alternative-specific parameters* to specify assumptions for each alternative. The minimum, maximum, and mean values of the intervals were used, according to the results of the consistency and cluster analyses. Table 5 shows a quantitative description of the three alternatives within the two scenarios.

After the completed data collection using SP follows ESA with the comprehensive *Model development, Implementation, and Validation*: The performance scores shown in Table 6 for the individual criteria were calculated using various energy system models (see Table 3) developed within the project (more information on the data exchange between the sub-models can be found in (Schwarz et al., 2018)). Renewable energy technologies are modeled with current efficiencies, i.e., without future potential efficiency gains (Arvidsson et al., 2017). Technologies that may become available in the future, such as carbon dioxide capture and storage (CCS), are also not included. The applied energy system models can be classified into micro-level and macro-level (Fig. 4 also elucidates the

Table 2
Projections of key factors in NEDS system scenarios.

Scenario Key factor	S1: High share of renewable energy technologies, but also fossil-fueled power plants as backup	S2: Successful energy transition supported by the general public	S3: Intelligent demand with economic growth	S4: Consumer-driven energy transition with stagnating economy	S5: Energy transition without support from the general public
1: Topology of power plants	Focus on distributed, large renewable power plants (e.g., offshore wind parks)	Focus on local power plants (e.g., photovoltaic power plants on rooftops)	Focus on conventional central power plants	Focus on local power plants (e.g., photovoltaic power plants on rooftops)	Focus on distributed small renewable power plants (e.g., wind or photovoltaic power plants)
2: Energy mix	High share of renewable energy technologies, but with fossil-fueled power plants as backup	High share of renewable energy technologies	No significant change	High share of renewable energy technologies	High share of renewable energy technologies
3: Levelized cost of electricity	Fossil-fueled power plants remain competitive	Renewable energy technologies are cheaper	Fossil-fueled power plants remain competitive	Increasing costs for fossil power plants	Renewable energy technologies are cheaper
4: Power grid	Significant expansion of power lines	Intelligent replacement of equipment allows for less expansion of power lines	No expansion of power lines, no replacement of equipment	Significant expansion of power lines	Significant expansion of power lines and replacement of equipment
5: Digitalization in the distribution grid	No digitalization	Significant digitalization	Significant digitalization	Lost opportunity (ICT infrastructure missing in the distribution grid)	Significant digitalization
6: Energy management	Energy supply and demand are not flexible	Energy supply and demand are flexible in both private households and industry	Energy supply and demand are flexible in both private households and industry	Energy supply and demand are flexible in both private households and industry	Energy supply and demand are flexible in the industry
7: Energy demand (private households)	Little advances in energy efficiency, demand not reduced	Very efficient electrical devices, increasing number of devices	Very efficient electrical devices, increasing number of devices	Very efficient electrical devise, decreasing number of devices	Little advances in energy efficiency, demand not reduced
8: Economy and its energy demand	Economic stagnation, high energy intensity	Economic growth, low energy intensity	Economic growth, high energy intensity	Economic stagnation, high energy intensity	Economic growth, low energy intensity
9: Energy policy and international coordination	Strong regulation of energy markets, low coordination in the European Union	Little regulation of energy markets, high coordination in the European Union	National energy markets, low coordination in the European Union	European standards, taxes, and regulations	Little regulation of energy markets, high coordination in the European Union
10: Knowledge and perceived control	Potential of technological progress is not used	New technologies are used efficiently	New technologies are used efficiently	New technologies are used efficiently	Significant diffusion of knowledge about technologies, but insufficient perceived control
11: Acceptance	Local opposition against energy projects	Energy transition is supported by the general public	Opportunistic behavior	Energy transition is supported by the general public	Local opposition against energy projects

input and output data, system boundaries, and sub-models that were used in the case study.):

On the micro-level, a qualitative user behavior model (Reinhold et al., 2018) details citizens' use of time in Germany in 2012 and 2013, based on an empirical investigation (Statistisches Bundesamt, 2018b) as well as on an empirical survey of behavior adaption costs. A smart-home simulation model (Reinhold and Engel, 2017) addresses the power flows inside residential buildings and considers options for demand management, electricity production by photovoltaics, and energy storage systems. The smart grid model (Nieße and Tröschel, 2016) is a multi-agent simulation model, which coordinates and optimizes the electricity supply and demand across multiple residential buildings in a smart grid, under consideration of the behavior adaption costs. The smart home and smart grid models are coupled in a co-simulation (Schwarz et al., 2018) and provide the power generation and demand on the low voltage level of the power grid in Lower Saxony.

On the macro-level, a dispatch model for the operation of power plants models the power flows in the European Network of Transmission System Operators (ENTSO-E) and matches supply and demand in the European electricity market (Rendel, 2015). Based on the unit commitment, a power grid optimization model calculates necessary extensions of the power grid on medium and high voltage levels (Blaufuß and Hofmann, 2018). Based on the energy mix, necessary grid extension, and impact indicators obtained from Ecoinvent (2018), a life cycle assessment (LCA) model calculates environmental impacts. Finally, a macroeconomic market model in the form of a computable general equilibrium model analyzes the effects of climate policies and trade policies (Pothen and Hübler, 2018).

The *determination of the performance scores* for each alternative on each criterion in each external scenario is based on the results of the various energy system sub-models. The performance scores can be found in the decision table for Scenario 1 and 2 (see Table 6).

For MCA, the outranking method PROMETHEE is applied to *aggregate the decision matrix* (Brans and Smet, 2016; Brans and Vincke, 1985). PROMETHEE starts with a pairwise comparison of two alternatives' $a_j \in A = \{a_1, a_2, \ldots, a_m\}$ performance scores $c_i(a_j) =: x_{ij}$ on each criterion $c_i \in C = \{c_1, c_2, \ldots, c_n\}$. Depending on the criterion, the performance scores can be minimized or maximized. For example, a maximization is assumed for the criterion *percentage of plants utilizing renewable energies*. An increase in the share of electricity production by renewable plants is therefore assumed to be positive. Contrary to this, a minimization of the criterion *global warming potential,* means that the less emissions contributing to the global warming potential, the better. The differences $d_i(a_j, a_k) = x_{ij} - x_{ik}$ are used as input for one of six generic preference functions P_i, which model different intra-criteria preferences. Some of these preference functions require the definition of preference thresholds p_i, q_i, and σ_i. Aggregating the results of the

Table 3
Criteria hierarchy for evaluating Lower Saxony's power system. The last column indicates, which models developed in the project were used to calculate the performance scores.

Sub-Objective	Criteria	Unit	Associated Models
Technical	Percentage of plants utilizing renewable energies	%	Blaufuβ and Hofmann (2018)
	Grid efficiency	share of output %	
Social	Import quota for energy sources used	%	Pothen and Hübler (2018)
	Ratio of wage to capital income	%	
	Share of expenditure on electricity of total consumption expenditure	%	
	Behavioral adaption costs	€/capita	Reinhold et al. (2018)
	Particulate matter formation	kg PM10-eq/MWh	Life cycle assessment of the power system based on energy production and transmission grid expansion calculated by Blaufuβ and Hofmann (2018) and impact indicators obtained from Ecoinvent (2018)
	Photochemical oxidant formation	kg NMVOC/MWh	
	Human toxicity	kg 1,4-DCB-eq/MWh	
Environmental	Metal depletion	kg Fe-eq/MWh	
	Fossil depletion	kg oil-eq/MWh	
	Global Warming Potential	kg CO2-eq/MWh	
	Terrestrial acidification	kg SO2-eq/MWh	
	Freshwater eutrophication	kg P-eq/MWh	
	Terrestrial ecotoxicity	kg 1,4-DCB-eq/MWh	
	Agricultural land occupation	m^2/MWh	
Economic	Real gross domestic product	1000 €/capita	Pothen and Hübler (2018).
	Costs of electricity production and grid expansion	€/MWh	Blaufuβ and Hofmann (2018)

Table 4
Examples for parameter values for 2050 in two selected scenarios.

	S1: High share of renewable energy technologies but also fossil-fueled power plants as backup	S2: Successful energy transition supported by the general public	Data Sources
Alternative-specific parameters			
Onshore wind energy (in GW)	[23.42; 26.93]	[22.14; 23.87]	Faulstich et al. (2016)
Offshore wind energy (in GW)	[14.41; 17.92]	[9.20; 10.93]	Faulstich et al. (2016)
Photovoltaic on rooftops (in GW)	[4.16; 28.02]	[18.83; 23.75]	Faulstich et al. (2016)
Photovoltaic in open area (in GW)	[25.07; 48.92]	[18.72; 23,64]	Faulstich et al. (2016)
Total capacity of energy storage systems (all voltage levels) (in TWh)	[4.11; 12.33]	[6.7; 8.2]	Faulstich et al. (2016)
Share of households in the smart grid (in %)	[10; 22]	[50; 67]	Own assumption
Scenario-specific parameters			
Price for crude oil (in USD)	85	140	(International Energy Agency, 2016)
Price for natural gas (in USD)	10	14	International Energy Agency (2016)
Economic growth rate (in %)	0,3	1	International Energy Agency (2016)
Private households with energy management (in %)	15	75	Own assumption
General parameters			
Population	9,450,000	9,450,000	Faulstich et al. (2016)
Distance between wind energy power plants and residential areas (in m)	400	400	Faulstich et al. (2016)
Lifetime of wind energy power plants (onshore and offshore) (in years)	20	20	Faulstich et al. (2016)

comparisons over all criteria with weights w_i (with $\sum_{i=1}^{n} w_i = 1$) yields the outranking relations (4.1).

$$(a_j, a_k) = \sum_{i=1}^{n} w_i \cdot P_i(a_j, a_k) \tag{4.1}$$

Aggregating the outranking relations over all other alternatives $a \in A \backslash a_j$ yields positive and negative outranking flows:

$$\varphi^+(a_j) = \frac{1}{m-1} \cdot \sum_{a \in A} \pi(a_j, a) \tag{4.2}$$

Table 5
Quantification of alternative-specific parameters.

	S1: High share of renewable energy technologies but also fossil-fueled power plants as backup			S2: Successful energy transition supported by the general public		
	A1	A2	A3	A1	A2	A3
Alternative-specific parameters						
Onshore wind energy (in GW)	26.93	23.42	25.18	23.87	22.14	23.58
Offshore wind energy (in GW)	14.41	17.92	16.16	9.20	10.93	9.49
Photovoltaic on rooftops (in GW)	28.02	4.16	16.08	23.75	18.83	21.76
Photovoltaic in open area (in GW)	25.07	48.92	37.00	18.72	23.64	20.70
Total capacity of energy storage systems (all voltage levels) (in TWh)	12.33	4.11	8.22	6.70	8.20	7.45
Share of households in the smart grid (in %)	22	10	16	67	50	58.5

Table 6
Decision Table for the two selected scenarios and three respective alternatives.

				Scenario 1: High share of renewable energy technologies, but also fossil-fueled power plants as backup				Scenario 2: Successful energy transition supported by the general public[a]			
Sub-Objective	Criteria	Unit	Objective	S1 A1	S1 A2	S1 A3	Preference threshold	S2 A1	S2 A2	S2 A3	Preference threshold
Technical	Percentage of plants utilizing renewable energies	%	max	0.929	0.942	0.943	0.014	1.000	1.000	1.000	0.000
	Grid efficiency	share of output %	max	0.960	0.960	0.960	0.000	0.955	0.965	0.964	0.010
Social	Import quota for energy sources used	%	min	0.031	0.031	0.039	0.008	0.000	0.000	0.000	0.000
	Ratio of wage to capital income	%	min	1.002	1.001	1.001	0.001	0.965	0.964	0.966	0.003
	Share of expenditure on electricity of total consumption expenditure	%	min	0.010	0.010	0.010	0.000	0.008	0.008	0.008	0.000
	Behavioral adaptation costs	€/capita	min	1.822	0.107	0.898	1.715	2.022	0.607	1.198	1.415
	Particulate matter formation	kg PM10-eq/MWh	min	0.231	0.214	0.220	0.017	0.230	0.227	0.231	0.004
	Photochemical oxidant formation	kg NMVOC/MWh	min	0.283	0.272	0.274	0.012	0.274	0.271	0.277	0.006
	Human toxicity	kg 1,4-DCB-eq/MWh	min	93.434	82.031	87.762	11.402	100.933	97.469	100.319	3.464
Environmental	Metal depletion	kg Fe-eq/MWh	min	19.472	18.104	19.010	1.367	21.954	21.424	21.782	0.531
	Fossil depletion	kg oil-eq/MWh	min	29.633	27.114	27.005	2.628	18.176	17.983	18.386	0.403
	Climate change	kg CO2-eq/MWh	min	90.876	84.796	84.556	6.320	65.833	65.339	66.601	1.262
	Terrestrial acidification	kg SO2-eq/MWh	min	0.785	0.671	0.706	0.114	0.698	0.692	0.700	0.008
	Freshwater eutrophication	kg P-eq/MWh	min	0.070	0.062	0.065	0.008	0.067	0.065	0.067	0.002
	Terrestrial ecotoxicity	kg 1,4-DCB-eq/MWh	min	0.097	0.095	0.096	0.003	0.109	0.108	0.111	0.003
	Agricultural land occupation	m^2/MWh	min	5.457	4.963	5.137	0.494	5.442	5.388	5.480	0.092
Economic	Real gross domestic product	1000 €/capita	max	42.508	42.57	42.54	0.06	55.683	55.857	55.770	0.174
	Costs of electricity production and grid expansion	€/MWh	min	69.377	68.104	67.866	1.511	34.258	27.240	27.908	7.018

[a] As a complete calculation for Scenario 2 was not possible in the scope of the project, the values have to a large extent been estimated considering the results obtained in Scenario 1.

$$\varphi^-(a_j) = \frac{1}{m-1} \cdot \sum_{a \in A} \pi(a,\ a_j) \tag{4.3}$$

The positive outranking flow (4.2) represents how much an alternative dominates all the other alternatives. The negative outranking flow (4.3) represents how much it is dominated by all the other alternatives, respectively. With PROMETHEE I, these positive and negative outranking flows can be used to create a partial ranking of alternatives, where two alternatives can be considered incomparable.

$$\varphi(a_j) = \varphi^+(a_j) - \varphi^-(a_j) \tag{4.4}$$

Aggregating $\varphi^+(a_j)$ and $\varphi^-(a_j)$ to the net outranking flow in (4.4), also called PROMETHEE II, yields a complete ranking. According to this, an alternative a_j is preferred to an alternative a_k if $\varphi(a_j) > \varphi(a_k)$.

For the application of PROMETHEE, the preferences of relevant stakeholders (e.g., politicians and citizens) should be elicited. One aim of the second NEDS symposium was to obtain subjective weights from the interviewed stakeholders. From the obtained answers, it was however not possible to establish exact numerical weights. In addition, the citizen sample at the symposium does not necessarily represent the general public, since the level of participation was rather low. For a first model run, we therefore assume equal weights for the sub-objectives, and equal weights for the criteria within each sub-objective. These weights are also in line with the original recommendations of the Enquête-Commission for a sustainable society, which recommended regarding the dimensions of sustainability as equal (Enquete-Kommission Umwelt,

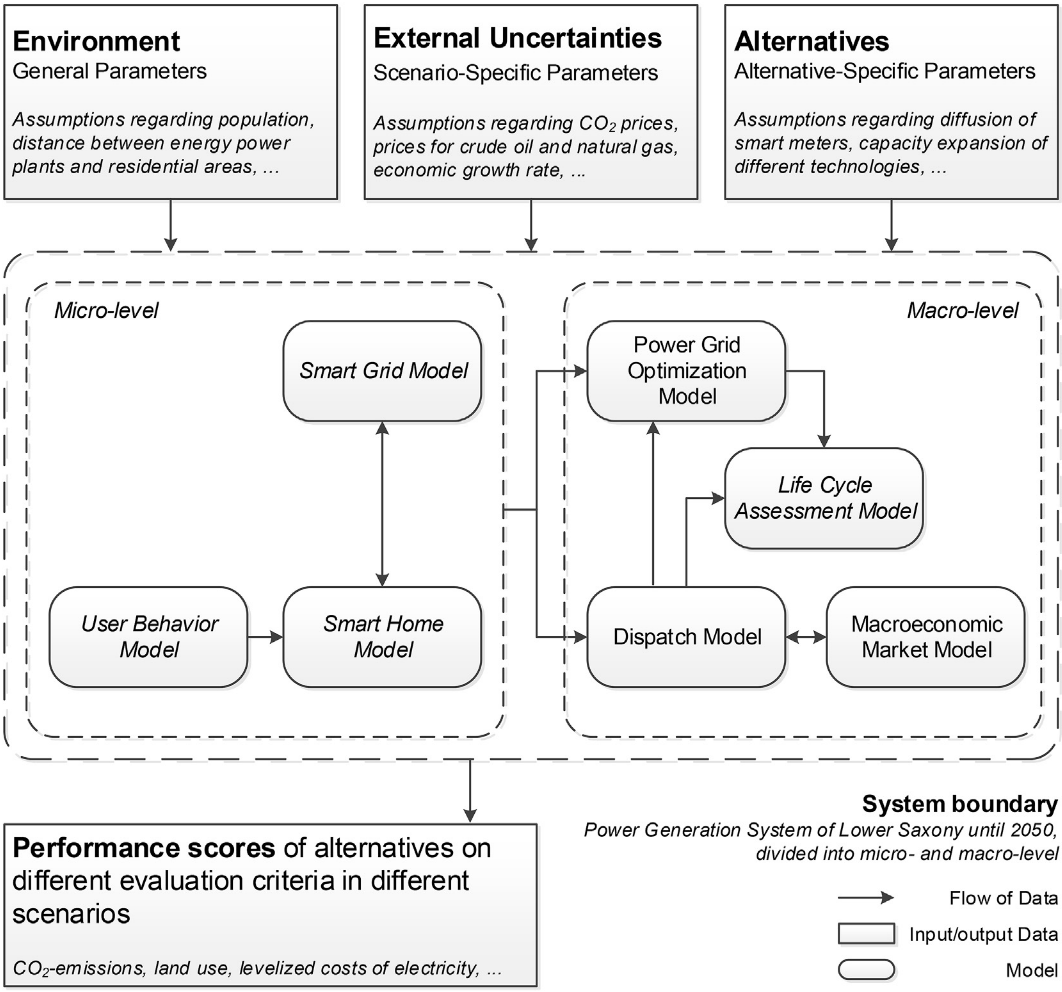

Fig. 4. Input/output data, system boundary, and models. Examples from the case study are set in italics.

1998) as well as current life cycle assessment literature (see, e.g., Tarne, et al., 2019).

The preference function of Type III (Brans and Vincke, 1985) was selected for each of the defined criteria. The required preference thresholds p_i were determined using the maximum difference between performance scores of all alternatives, following Tsoutsos et al. (2009). In scenario S2 (Successful energy transition supported by the general public), the sub-criteria "*percentage of power plants utilizing renewable energies*" and "*import quota for energy sources used*" do not have an impact, as the performance scores of all alternatives on these criteria are equal. The PROMETHEE method yields complete rankings (PROMETHEE II) for both scenarios as provided in Fig. 5. In this first model run, the centralized energy system comes off as the best alternative, in comparison to the other two, in both defined scenarios.

A *sensitivity analysis of criteria weights* is conducted to analyze their effect on the rankings. One option is to set all sub-criteria weights equal, in which case every sub-criterion has a weight of 5.56%. The performance scores and preference thresholds remain the same as in the initial configuration (see Table 6). The changes in the weights have an impact on the ranking of alternatives (see Fig. 6). In scenario S2, alternative A3 performs worse than the first alternative. Alternative A2, however, still comes off best and performs significantly better than the other two alternatives in both scenarios.

Finally, *conclusions and recommendations can be drawn* in a transparent way for the future development of the real power generation system in Lower Saxony. Fig. 6 shows that the evaluation of the three alternatives can differ according to the considered scenarios. In this illustrative case study, the second alternative (decentralized energy system) comes off as the best alternative (see Figs. 5 and 6), which can largely be attributed to its superiority in both the social and environmental dimensions.

5. Discussion

Energy system analysis is typically used to support decisions in the energy sector and energy policy with quantitative data. In this section, we discuss the benefits and limitations of the proposed framework combining energy system analysis (ESA) with Scenario Planning (SP) and with multi-criteria analysis (MCA), based on our findings in the case study. As elaborated in Table 1, there are many potential benefits when combining SP, ESA, and MCA.

The integration of the structured Scenario Planning (SP) method according to Gausemeier et al. (1998) allows defining alternatives and external uncertainties in a systematic way, so that key factors for the decision Problem can be taken into account. These key factors are split into influenceable and non-influenceable developments. All developments need to be internally consistent in order to form a scenario. Thereby, SP offers an approach to

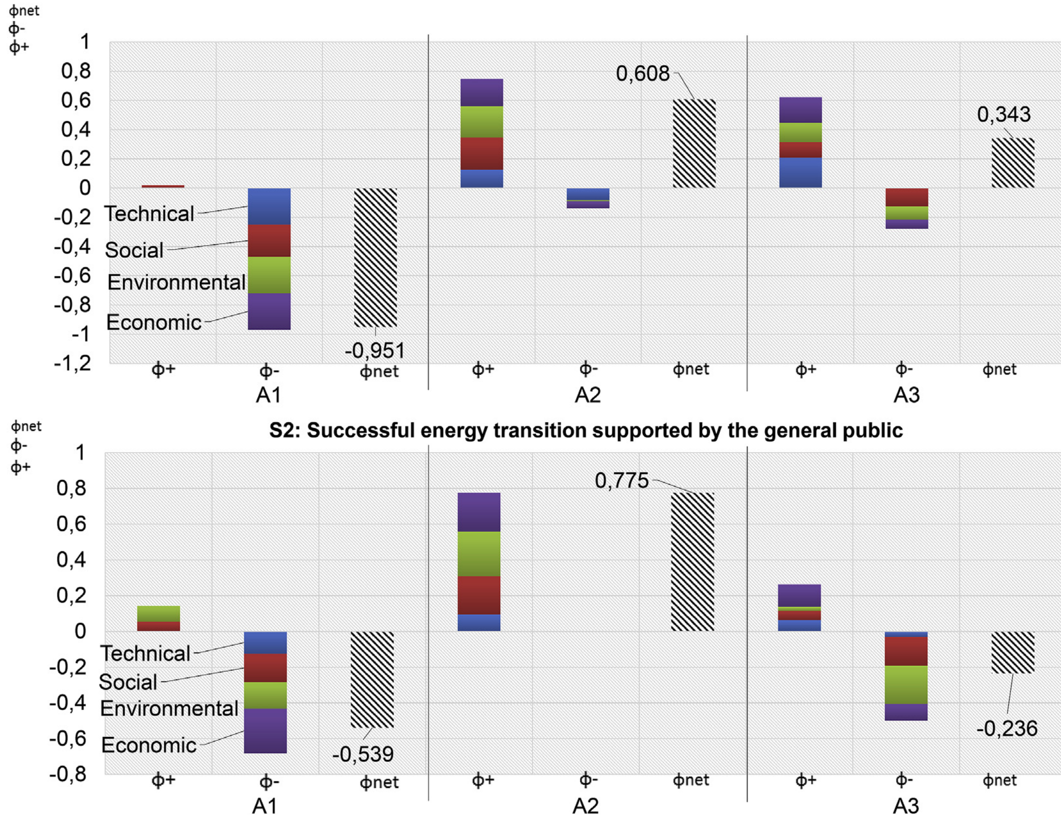

Fig. 5. PROMETHEE results for two selected scenarios, according to the sustainability dimensions for the alternatives A1 (decentralized energy system), A2 (centralized energy system), and A3 (mix of both). Equal weights (25%) are set for each of the sustainability dimensions.

investigate uncertainties, because it allows considering higher-order interactions of the key factors (Dieckhoff et al., 2014; Stewart and Durbach, 2016; Weimer-Jehle et al., 2016). Therefore, the fallacy of investigating particular assumptions for uncertain parameters, which are however not consistent with the assumptions in the scenario, can be avoided. The conversion of qualitative storylines from SP into quantitative assumptions will remain subjective, since there is no objective way to select specific parameter values (Schönfelder et al., 2011; Weimer-Jehle et al., 2016). Therefore, the process of specifying the assumptions should be documented carefully.

Next, the integration of multi-criteria analysis (MCA) appears to be valuable, not only for the aggregated evaluation (Stewart, 2019). An important contribution is that, by identifying relevant alternatives, evaluation criteria, and uncertainties, the decision Problem can be structured in such a way that it is represented in a decision table, which only encompasses decision-relevant information in a transparent way. Thus, a discussion about the advantages and disadvantages of different alternatives, which is usually driven by different stakeholders' interests and therefore sometimes neglecting important criteria, can be structured with this decision table. Next to problem structuring, another advantage is that aggregating this decision table leads to a clearer understanding of the alternatives' strengths and weaknesses, e.g., in terms of the sustainability dimensions, in different scenarios. For example, the results in the case study can be used to question why some alternatives come off better than others. If decentralized solutions for the energy transition are desired in the political debate, but are dominated by centralized solutions, it should be deliberated whether and how their weaknesses can be mitigated, or their strengths can be developed in comparison to other alternatives.

The application of the framework in the case study also reveals some challenges. It could be observed, that combining SP, ESA, and MCA requires significant efforts for coordination in the project team, because of many iterations of process steps. Furthermore, trying to involve stakeholders is at least difficult and the involvement of the general public with symposiums may not be suitable in these process steps. Even if there is a potentially large number of stakeholders, only selected, particularly interested stakeholders took part in the decision support process. Interactive workshops may be a more appropriate format for stakeholder involvement. In any case, the results of the energy scenario development and evaluation should be made publicly available. Because of the high complexity of the whole process of energy scenario development and evaluation and to avoid "cherry picking fallacy" (Hansson, 2016), it is crucial that both the results and the applied methods that led to them are documented in a suitable way (Grunwald et al., 2016). Especially, the underlying assumptions regarding alternatives, scenarios, and energy system models, and the process leading to the selection of evaluation criteria need to be made transparent.

Special attention regarding the system boundaries is necessary. Our case study was limited to planning of the electricity system of a federal state. Open questions concern the delimitation of neighboring areas or national or supranational requirements, such as EU-wide energy policy measures or transboundary energy transmission. General recommendations cannot be given, but system boundaries must be considered case-specific in the framework's application.

While, in general, the results obtained from the integration of SP, ESA, and MCA can provide orientation for decisions in energy policy, the results obtained from the illustrative case study presented above were obtained for only two selected scenarios and

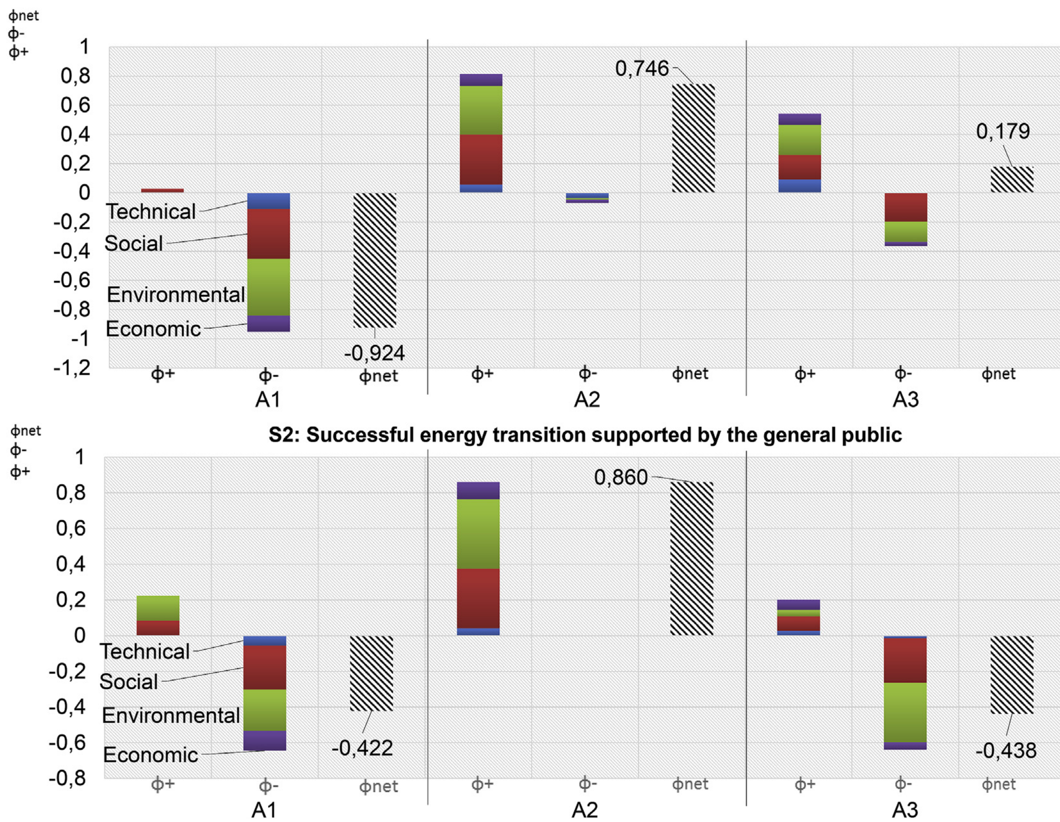

Fig. 6. PROMETHEE results for two selected scenarios with equal weights (5.56% per sub-criterion) for the alternatives A1 (decentralized energy system), A2 (centralized energy system), and A3 (mix of both).

three alternatives. For a more comprehensive evaluation and decision support, the method needs to be applied to evaluate alternatives in more scenarios. Furthermore, in accordance with the system boundaries, the different energy system models in this case study only represent selected parts of the power supply system and, consequently, the criteria hierarchy and performance scores used for the evaluation can only support decisions concerning the corresponding parts of the system. In addition, the calculated performance scores are based on current data, as the future technological developments until the year 2050 are unknown. Therefore, the uncertainty of parameters could be investigated in more detail, particularly for those parameters with a high impact on the performance scores, by specifying suitable parameter ranges and employing a robustness concept, leading to more robust performance scores.

6. Conclusion

This paper presents a framework for integrating scenario planning (SP), energy system analysis (ESA), and multi-criteria analysis (MCA) for the evaluation of future energy systems in terms of sustainability, competitiveness, and supply security. Specifically, SP allows creating energy scenarios in a transparent and systematic way, so that assumptions for alternatives and external scenarios are internally consistent. ESA provides quantitative modelling of the alternatives in different scenarios, while MCA supports Problem structuring by helping to identify relevant alternatives, scenarios, and evaluation criteria. MCA also allows for a more balanced and objective evaluation of alternative energy systems in terms of multiple criteria, which can be used to inform discussions among stakeholders and may thus increase acceptance. Thus, the combination of the three methods provides a more transparent and traceable decision support process for the development and evaluation of energy scenarios. The proposed framework was applied to an illustrative case study on planning the transition of the power generation system in Lower Saxony toward higher shares of renewable energy until 2050.

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References

Alcamo, J., 2008. The SAS approach: combining qualitative and quantitative knowledge in environmental scenarios. In: Alcamo, J. (Ed.), Environmental Futures. The Practice of Environmental Scenario Analysis, first ed. Elsevier, Amsterdam, Boston, pp. 123–150.

Antunes, C.H., Henriques, C.O., 2016. Multi-objective optimization and multi-criteria analysis models and methods for problems in the energy sector. In: Greco, S., Ehrgott, M., Figueira, J. (Eds.), Multiple Criteria Decision Analysis. State of the Art Surveys. Springer, New York.

Arvidsson, R., Tillman, A.M., Sandén, B., Janssen, M., Nordelöf, A., Kushnir, D., Molander, S., 2017. Environmental assessment of emerging technologies: recommendations for prospective LCA. J. Ind. Ecol. 22, 1286–1294. https://doi.org/10.1111/jiec.12690.

Belton, V., Stewart, T.J., 2003. Multiple Criteria Decision Analysis: an Integrated Approach, second ed. Kluwer Academic Publishers, Boston, Mass., p. 372

Blaufuß, C., Hofmann, L., 2018. Methodik zur Optimierung des Netzausbaus in beanspruchten Verteilnetzen. Leibniz Universität Hannover. ETG-CIRED-

Workshop 2018 (D-A-CH). Innovationen im Verteilnetz, Berlin, 2018.
Blaufuß, C., Dumeier, M., Kleinau, M., Krause, H., Minnemann, J., Nebel-Wenner, M., Reinhold, C., Schwarz, J.S., Wille, F., Witt, T., Busse, C., Eggert, F., Engel, B., Geldermann, J., Hofmann, L., Hübler, M., Lehnhoff, S., Sonnenschein, M., Seidel, J., 2019. Development of a Process for Integrated Development and Evaluation of Energy Scenarios for Lower Saxony – Final Report of the Research Project NEDS – Nachhaltige Energieversorgung Niedersachsen. Cuvillier, Göttingen, forthcoming.
Brans, J.-P., Smet, Y. de, 2016. PROMETHEE methods. In: Greco, S., Ehrgott, M., Figueira, J. (Eds.), Multiple Criteria Decision Analysis. State of the Art Surveys. Springer, New York, pp. 187–219.
Brans, J.P., Vincke, P., 1985. Note-a preference ranking organisation method: the PROMETHEE method for multiple criteria decision-making. Manag. Sci. 31, 647–656. https://doi.org/10.1287/mnsc.31.6.647.
Browne, D., O'Regan, B., Moles, R., 2010. Use of multi-criteria decision analysis to explore alternative domestic energy and electricity policy scenarios in an Irish city-region. Energy 35, 518–528. https://doi.org/10.1016/j.energy.2009.10.020.
Bundesnetzagentur, 2015. EEG statistical reports and "EEG in numbers". https://www.bundesnetzagentur.de/EN/Areas/Energy/Companies/RenewableEnergy/Facts_Figures_EEG/FactsFiguresEEG_node.html.
Bundesnetzagentur, Bundeskartellamt, 2016. Monitoringbericht 2016: Monitoringbericht gemäß § 63 Abs. 3 i.V.m. § 35 EnWG und § 48 Abs. 3 i.V.m. § 53 Abs. 3. GWB, Bonn.
Cao, K.-K., Cebulla, F., Gómez Vilchez, J.J., Mousavi, B., Prehofer, S., 2016. Raising awareness in model-based energy scenario studies—a transparency checklist. Energy Sustain. Soc. 6, 1–20. https://doi.org/10.1186/s13705-016-0090-z.
Comes, T., Hiete, M., Schultmann, F., 2013. An approach to multi-criteria decision problems under severe uncertainty. J. Multi-Criteria Decis. Anal. 20, 29–48. https://doi.org/10.1002/mcda.1487.
Diakoulaki, D., Karangelis, F., 2007. Multi-criteria decision analysis and cost–benefit analysis of alternative scenarios for the power generation sector in Greece. Renew. Sustain. Energy Rev. 11, 716–727.
Dieckhoff, C., Appelrath, H.-J., Fischedick, M., Grunwald, A., Höffler, F., 2014. Zur Interpretation von Energieszenarien. acatech - Deutsche Akademie der Technikwissenschaften, München.
Durbach, I.N., Stewart, T.J., 2003. Integrating scenario planning and goal programming. J. Multi-Criteria Decis. Anal. 12, 261–271. https://doi.org/10.1002/mcda.362.
Durbach, I.N., Stewart, T.J., 2012. Modeling uncertainty in multi-criteria decision analysis. Eur. J. Oper. Res. 223, 1–14. https://doi.org/10.1016/j.ejor.2012.04.038.
Ecoinvent, 2018. „Ecoinvent Version 3.4" Swiss Centre for Life Cycle Inventories (Ecoinvent), St. Gallen.
Enquete-Kommission Umwelt, 1998. Abschlußbericht der Enquete-Kommission „Schutz des Menschen und der Umwelt - Ziele und Rahmenbedingungen einer nachhaltig zukunftsverträglichen Entwicklung.
Faulstich, M., Beck, H.-P., Haaren, C., von Kuck, J., Rode, M., Ahmels, J., Dossola, F., Zum Hingst, J., Kaiser, F., Kruse, A., Palmas, C., Römer, G., Ryspaeva, I., Schmidt-Kanefendt, H.-H., Siemers, W., Simons, R., Springmann, J.-P., Yilmaz, C., 2016. Szenarien zur Energieversorgung in Niedersachsen im Jahr 2050: Gutachten. Niedersächsisches Ministerium für Umwelt Energie und Klimaschutz, Hannover.
French, S., 1995. Uncertainty and imprecision: modelling and analysis. J. Oper. Res. Soc. 46, 70–79. https://doi.org/10.1057/jors.1995.8.
French, S., Geldermann, J., 2005. The varied contexts of environmental decision problems and their implications for decision support. Environ. Sci. Policy 8, 378–391. https://doi.org/10.1016/j.envsci.2005.04.008.
Gal, T., Stewart, J.T., Hanne, T., 1999. Multicriteria Decision Making Advances in MCDM Models, Algorithms, Theory, and Applications. Kluwer Academic Publishers, Boston.
Gausemeier, J., Fink, A., Schlake, O., 1998. Scenario management: an approach to develop future potentials. Technol. Forecast. Soc. Chang. 59, 111–130.
Goodwin, P., Wright, G., 2001. Enhancing strategy evaluation in scenario planning: a role for decision analysis. J. Manag. Stud. 38, 1–16. https://doi.org/10.1111/1467-6486.00225.
Greco, S., Ehrgott, M., Figueira, J. (Eds.), 2016. Multiple Criteria Decision Analysis: State of the Art Surveys. Springer, New York.
Grimble, R., Wellard, K., 1997. Stakeholder methodologies in natural resource management: a review of principles, contexts, experiences and opportunities. Agric. Syst. 55, 173–193. https://doi.org/10.1016/S0308-521X(97)00006-1.
Grunwald, A., 2011. Der Lebensweg von Energieszenarien - umrisse eines Forschungsprogramms. In: Dieckhoff, C., Fichtner, W., Grunwald, A., Meyer, S., Nast, M., Nierling, L., Renn, O., Voß, A., Wietschel, M. (Eds.), Energieszenarien. Konstruktion, Bewertung und Wirkung - „Anbieter" und „Nachfrager" im Dialog. KIT Scientific Publishing, Karlsruhe, pp. 11–24.
Grunwald, A., Dieckhoff, C., Fischedick, M., Höffler, F., Mayer, C., Weimer-Jehle, W., 2016. Consulting with energy scenarios: Requirements for scientific policy advice. Monograph Series on Science-based Policy Advice. acatech - Deutsche Akademie der Technikwissenschaften e. V., München.
Hake, J.-F., Kleemann, M., Kuckshinrichs, W., Jülich, Forschungszentrum, 1994. Modelling of energy-related emissions on a national and global level: an overview of selected approaches. In: Hake, J.-F. (Ed.), Advances in System Analysis. Modelling Energy Related Emissions on a National and Global Level. Forschungszentrum Zentralbibliothek, Jülich, pp. 1–26.
Hansson, S.O., 2016. Evaluating the uncertainties. In: Hansson, S.O., Hirsch Hadorn, G. (Eds.), The Argumentative Turn in Policy Analysis - Reasoning about Uncertainty. Springer, Cham, pp. 79–104.
International Energy Agency, 2016. World Energy Outlook 2016: Executive Summary. International Energy Agency, Paris. http://www.iea.org/newsroom/news/2016/november/world-energy-outlook-2016.html. Accessed 1 December 2016.
Jovanović, M., Afgan, N., Radovanović, P., Stevanović, V., 2009. Sustainable development of the Belgrade energy system. Energy 34, 532–539. https://doi.org/10.1016/j.energy.2008.01.013.
Kahn, H., Wiener, A.J., 1967. The Year 2000: A Framework for Speculation on the Next Thirty-Three Years. Macmillan, New York.
Karvetski, C.W., Lambert, J.H., Keisler, J.M., Linkov, I., 2011. Integration of decision analysis and scenario planning for coastal engineering and climate change. IEEE Trans. Syst., Man, Cybern. A 41, 63–73. https://doi.org/10.1109/TSMCA.2010.2055154.
Keeney, R.L., 1992. Value-focused Thinking: A Path to Creative Decisionmaking. Harvard University Press, Cambridge, Mass, p. 416.
Kowalski, K., Stagl, S., Madlener, R., Omann, I., 2009. Sustainable energy futures: methodological challenges in combining scenarios and participatory multi-criteria analysis. Eur. J. Oper. Res. 197, 1063–1074. https://doi.org/10.1016/j.ejor.2007.12.049.
Küll, R., Stähly, P., 1999. Zur Planung und effizienten Abwicklung von Simulationsexperimenten. In: Biethahn, J., Hummeltenberg, W., Schmidt, B., Stähly, P., Witte, T. (Eds.), Simulation als betriebliche Entscheidungshilfe. State of the Art und neuere Entwicklungen. Physica-Verlag HD, Heidelberg, pp. 1–21.
Lerche, N., Wilkens, I., Schmehl, M., Eigner-Thiel, S., Geldermann, J., 2017. Using methods of Multi-Criteria Decision Making to provide decision support concerning local bioenergy projects. Soc. Econ. Plan. Sci. https://doi.org/10.1016/j.seps.2017.08.002.
Lund, H., Arler, F., Østergaard, P.A., Hvelplund, F., Connolly, D., Mathiesen, B.V., Karnøe, P., 2017. Simulation versus optimization: theoretical positions in energy system modelling. Energies 10, 1–17. https://doi.org/10.3390/en10070840.
MacQueen, J., 1967. Some methods for classification and analysis of multivariate observations. In: Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, vol. 1. University of California Press, Berkeley, USA, pp. 281–297. Statistics, Berkeley, California. June 21-July 18, 1965 and December 27, 1965-January 7, 1966.
Madlener, R., Kowalski, K., Stagl, S., 2007. New ways for the integrated appraisal of national energy scenarios: the case of renewable energy use in Austria. Energy Policy 35, 6060–6074. https://doi.org/10.1016/j.enpol.2007.08.015.
Marttunen, M., Lienert, J., Belton, V., 2017. Structuring problems for Multi-Criteria Decision Analysis in practice: a literature review of method combinations. Eur. J. Oper. Res. 263, 1–17. https://doi.org/10.1016/j.ejor.2017.04.041.
McKenna, R., Bertsch, V., Mainzer, K., Fichtner, W., 2018. Combining local preferences with multi-criteria decision analysis and linear optimization to develop feasible energy concepts in small communities. Eur. J. Oper. Res. 268, 1092–1110. https://doi.org/10.1016/j.ejor.2018.01.036.
Montibeller, G., Gummer, H., Tumidei, D., 2006. Combining scenario planning and multi-criteria decision analysis in practice. J. Multi-Criteria Decis. Anal. 14, 5–20. https://doi.org/10.1002/mcda.403.
Möst, D., Fichtner, W., 2009. Einführung zur Energiesystemanalyse. In: Möst, D., Fichtner, W., Grunwald, A. (Eds.), Energiesystemanalyse. Tagungsband des Workshops „Energiesystemanalyse" vom 27. November 2008 am KIT Zentrum Energie, Karlsruhe. Univ.-verl., Karlsruhe, pp. 11–32.
Nieße, A., Tröschel, M., 2016. Controlled self-organization in smart grids. In: ISSE 2016, Edinburgh, Scotland. 2016 International Symposium on Systems Engineering: George Hotel, October 3-5, 2016: Proceedings Papers. IEEE, Piscataway, NJ, pp. 1–6.
Oberschmidt, J., Geldermann, J., Ludwig, J., Schmehl, M., 2010. Modified PROMETHEE approach for assessing energy technologies. Int. J. Energy Sect. Manag. 4, 183–212. https://doi.org/10.1108/17506221011058696.
Pfenninger, S., Hawkes, A., Keirstead, J., 2014. Energy systems modeling for twenty-first century energy challenges. Renew. Sustain. Energy Rev. 33, 74–86. https://doi.org/10.1016/j.rser.2014.02.003.
Pothen, F., Hübler, M., 2018. The interaction of climate and trade policy. Eur. Econ. Rev. 107, 1–26. https://doi.org/10.1016/j.euroecorev.2018.04.004.
Reinhold, C., Engel, B., 2017. Simulation environment for investigations of energy flows in residential districts and energy management systems. In: Speh, R. (Ed.), International ETG Congress 2017. VDE Verlag, Berlin, Offenbach, pp. 102–106.
Reinhold, C., Wille, F., Engel, B., Eggert, F., 2018. Empirische und Synthetische Lastprognose von nutzerabhängigen Verbrauchsgeräten. In: 15. Symposium Energieinnovation, Graz, vol. 14, pp. 1–13, 16.02.2018.
Rendel, T., 2015. Erweiterung und Plausibilisierung eines Modells für die integrierte Simulation des europäischen Verbundnetzes und Strommarktes. Dissertation, Hannover.
Rosenhead, J. (Ed.), 1989. Rational Analysis for a Problematic World: Problem Structuring Methods for Complexity, Uncertainty and Conflict. Wiley, Chichester, p. 370.
Saltelli, A., 2007. Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models. Wiley, Hoboken, NJ, p. 219.
Schoemaker, P.J.H., 1995. Scenario Planning: a tool for strategic thinking. Sloan Manag. Rev. 36, 25–40.
Schönfelder, M., Jochem, P., Fichtner, W., 2011. Energiesystemmodelle zur Szenarienbildung - potenziale und Grenzen. In: Dieckhoff, C., Fichtner, W., Grunwald, A., Meyer, S., Nast, M., Nierling, L., Renn, O., Voß, A., Wietschel, M. (Eds.), Energieszenarien. Konstruktion, Bewertung und Wirkung - „Anbieter" und „Nachfrager" im Dialog. KIT Scientific Publishing, Karlsruhe, pp. 25–40.

Schwarz, J.S., Witt, T., Nieße, A., Geldermann, J., Lehnhoff, S., Sonnenschein, M., 2017. Towards an integrated sustainability evaluation of energy scenarios with automated information exchange. In: Proceedings of the 6th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS). SCITEPRESS, Setúbal, pp. 188−199. Porto. 22.04.2017 - 24.04.2017.
Schwarz, J.S., Witt, T., Nieße, A., Geldermann, J., Lehnhoff, S., Sonnenschein, M., 2018. Towards and integrated development and sustainability evaluation of energy scenarios assisted by automated information exchange. In: Donnellan, B., Klein, C., Helfert, M., Gusikhin, O., Pascoal, A. (Eds.), Smart Cities, Green Technologies, and Intelligent Transport Systems. SMARTGREENS 2017, VEHITS 2017. Springer, Cham, pp. 3−26.
Siebert, J., Keeney, R.L., 2015. Creating more and better alternatives for decisions using objectives. Oper. Res. 63, 1144−1158. https://doi.org/10.1287/opre.2015.1411.
Spronk, J., Steuer, R.E., Zopounidis, C., 2016. Multicriteria decision aid/analysis in finance. In: Greco, S., Ehrgott, M., Figueira, J. (Eds.), Multiple Criteria Decision Analysis. State of the Art Surveys. Springer, New York.
Statistisches Bundesamt, 2018a. Gebiet und Bevölkerung − fläche und Bevölkerung. https://www.destatis.de/DE/ZahlenFakten/LaenderRegionen/Regionales/Gemeindeverzeichnis/Administrativ/Aktuell/02Bundeslaender.xlsx?__blob=publicationFile. Accessed 29 November 2018.
Statistisches Bundesamt, 2018b. Zeitverwendungserhebung 2012/2013. On-Site, Version 0.
Steinhilber, S., Geldermann, J., Wietschel, M., 2016. Renewables in the EU after 2020: a multi-criteria decision analysis in the context of the policy formation process. EURO J. Decis. Process 4, 119−155. https://doi.org/10.1007/s40070-016-0060-x.
Sternberg, A., Bardow, A., 2015. Power-to-What?: environmental assessment of energy storage systems. Energy Environ. Sci. 8, 389−400. https://doi.org/10.1039/C4EE03051F.
Stewart, T.J., 2019. Multicriteria decision analysis as focus for strategic planning. In: 30th European Conference on Operational Research, 23rd - 26th June, Dublin, Ireland.
Stewart, T.J., Durbach, I.N., 2016. Dealing with uncertainties in MCDA. In: Greco, S., Ehrgott, M., Figueira, J. (Eds.), Multiple Criteria Decision Analysis. State of the Art Surveys. Springer, New York, pp. 467−496.
Stewart, T.J., French, S., Rios, J., 2013. Integrating multicriteria decision analysis and scenario planning—review and extension. OMEGA Int. J. Manag. Sci. 41, 679−688. https://doi.org/10.1016/j.omega.2012.09.003.
Tarne, P., Lehmann, A., Finkbeiner, M., 2019. Introducing weights to life cycle sustainability assessment—how do decision-makers weight sustainability dimensions? Int. J. Life Cycle Assess. 24 (3), 530−542. https://doi.org/10.1007/s11367-018-1468-2.
The Federal Government, 2016. German sustainable development strategy. https://www.bundesregierung.de/resource/blob/998220/455740/7d1716e5d5576bec62c9d16ca908e80e/2017-06-20-langfassung-n-en-data.pdf?download=1https://www.bundesregierung.de/resource/blob/975274/1546450/65089964ed4a2ab07ca8a4919e09e0af/2018-11-07-aktualisierung-dns-2018-data.pdf?download=1. Accessed 15 July 2019.
Trutnevyte, E., Stauffacher, M., Scholz, R.W., 2011. Supporting energy initiatives in small communities by linking visions with energy scenarios and multi-criteria assessment. Energy Policy 39, 7884−7895. https://doi.org/10.1016/j.enpol.2011.09.038.
Tsoutsos, T., Drandaki, M., Frantzeskaki, N., Iosifidis, E., Kiosses, I., 2009. Sustainable energy planning by using multi-criteria analysis application in the island of Crete. Energy Policy 37, 1587−1600. https://doi.org/10.1016/j.enpol.2008.12.011.
European Union, 2010. The Treaty on the Functioning of the European. TFEU, Union.
van der Pas, J.W.G.M., Walker, W.E., Marchau, V.A.W.J., van Wee, G.P., Agusdinata, D.B., 2010. Exploratory MCDA for handling deep uncertainties: the case of intelligent speed adaptation implementation. J. Multi-Criteria Decis. Anal. 17, 1−23. https://doi.org/10.1002/mcda.450.
Walker, W.E., Harremoës, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P., Krayer von Krauss, M.P., 2003. Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. Integr. Assess. 4, 5−17. https://doi.org/10.1076/iaij.4.1.5.16466.
Wang, J.-J., Jing, Y.-Y., Zhang, C.-F., Zhao, J.-H., 2009. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renew. Sustain. Energy Rev. 13, 2263−2278. https://doi.org/10.1016/j.rser.2009.06.021.
Weimer-Jehle, W., Buchgeister, J., Hauser, W., Kosow, H., Naegler, T., Poganietz, W.-R., Pregger, T., Prehofer, S., Recklinghausen, A. von, Schippl, J., Vögele, S., 2016. Context scenarios and their usage for the construction of socio-technical energy scenarios. Energy 111, 956−970. https://doi.org/10.1016/j.energy.2016.05.073.
Witt, T., Stahlecker, K., Geldermann, J., 2018. Morphological analysis of energy scenarios. Int. J. Energy Sect. Manag. 12, 525−546. https://doi.org/10.1108/IJESM-09-2017-0003.
Zimmermann, H.-J., 2000. An application-oriented view of modeling uncertainty. Eur. J. Oper. Res. 122, 190−198. https://doi.org/10.1016/S0377-2217(99)00228-3.
Zwicky, F., 1967. The morphological approach to discovery, invention, research and construction. In: Zwicky, F., Wilson, A.G. (Eds.), New Methods of Thought and Procedure. Contributions to the Symposium on METHODOLOGIES. Springer, Berlin, Heidelberg, New York, pp. 273−297.