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Article

Integrating Methods and Empirical Findings from Social and Behavioural Sciences into Energy System Models—Motivation and Possible Approaches

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Abstract: The transformation of the energy system is a highly complex process involving many dimensions. Energy system models help to understand the process and to define either target systems or policy measures. Insights derived from the social sciences are not sufficiently represented in energy system models, but address crucial aspects of the transformation process. It is, therefore, necessary to develop approaches to integrate results from social science studies into energy system models. Hence, as a result of an interdisciplinary discourse among energy system modellers, social scientists, psychologists, economists and political scientists, this article explains which aspects should be considered in the models, how the respective results can be collected and which aspects of integration into energy system models are conceivable to provide an overview for other modellers. As a result of the discourse, five facets are examined: Investment behaviour (market acceptance), user behaviour, local acceptance, technology innovation and socio-political acceptance. Finally, an approach is presented that introduces a compound of energy system models (with a focus on the macro and micro-perspective) as well as submodels on technology genesis and socio-political acceptance, which serves to gain a more fundamental knowledge of the transformation process.

Keywords: energy system modelling; social science; system optimisation; energy transition; investment behaviour; local acceptance; socio-political acceptance; technology genesis; user behaviour

1. Introduction

The need for a transformation of the energy system due to climate change led to the development of more models that provide insights and solutions for future energy systems concerning climate policy, the security of supply and economic developments [1]. Energy system models (ESM), which cover the entire energy system including the sectors for energy production, buildings, transport and industry from a techno-economic perspective, provide decision support [2]. Recently, the number of different energy and electricity market models has grown significantly. Ref. [3] gives an overview of 75 different models (with a focus on the electricity sector) in the current modelling landscape, which illustrates the central role ESM already play. Ref. [1] identifies the four main challenges of ESM being the computing time, uncertainty and transparency, growing complexity and integrating human behaviour, social risks and opportunities in ESM. Although [4] emphasises that energy transitions are a combination of technical, social and political factors, the field of social science is greatly underrepresented in energy system modelling [5–7]. Possible transformations of the energy system are mainly considered from a techno-economic perspective. To date, social factors have largely been neglected in ESM, thereby limiting the insights derived and, as such, the integration of social and behavioural factors would vastly improve the overarching messaging from ESM.

However, which specific aspects to include and how this can be done is not always straight-forward. Individual approaches, for example, exist that are focussed on the integration of acceptance into ESM [8,9]. Existing approaches concerning different aspects of social and behavoiural factors are presented based on the literature review. Based on already existing approaches, this article aims to provide a more generalised overview, to highlight which aspects of social science should be considered in ESM, which methods are suitable for this purpose and how these could be integrated. Furthermore, we will demonstrate how the coupling of different models can lead to a deeper understanding of the energy system interrelationships when taking social factors into account. The article reflects the results of an interdisciplinary discourse of scientists from the social science, psychology, economics, political science and energy system modelling disciplines and thus aims to support other energy system modellers on how to consider social science findings and methods in future work.

Figure 1 gives an overview of the article structure. In the following sections, we categorise and briefly describe ESMs from the macro and micro-perspectives. The extent of the integration of social science factors into these models is reviewed in the literature in Section 2. In Section 3, two socio-scientific agent-based models are presented, which represent the aspect of technology genesis on the one hand and socio-political acceptance on the other. Section 4 collates which factors should be taken into account in ESM from a social science perspective, and how they can be analysed and integrated into ESM at the macro and micro level. The different model categories answer different questions, but together they provide an even more fundamental understanding of the systemic relationships and complement each other well. Section 5, therefore, shows how the models of the different categories can be coupled. In Section 6, we summarise and discuss the main conclusions of the previous sections.

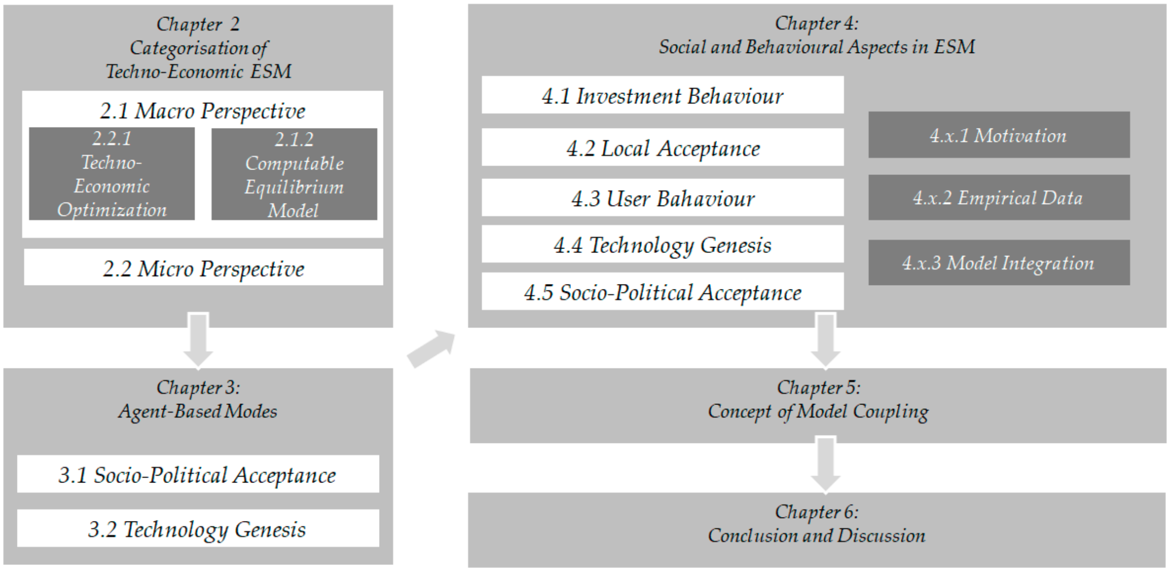

Figure 1. Overview of the article structure.

2. Categorisation of Techno-Economic Energy System Models

ESM answer different questions and therefore use different methods. Reviews of ESM can be found, for example, in [1,3,10–14], where, in addition to a categorisation of ESM, criteria for differentiating the models are listed. Ref. [1] (p. 4) divides the landscape of ESM into four categories: "*1. models covering the entire energy system, primarily using optimisation methods, with the primary aim of providing scenarios of how the system could evolve, 2. models covering the entire energy system, primarily using simulation techniques, with the primary purpose of providing forecasts of how the system may evolve, 3. models focused exclusively on the electricity system, ranging in methods and intentions from optimisation/scenarios to simulation/prediction, 4. scenarios relying on more qualitative or mixed methods rather than detailed mathematical models.*" For this article, the first two categories will be considered, since the need for integration of social science factors is particularly great here.

According to Ref. [15], the model landscape can be divided into top-down (economy-wide perspective; limited representation of the energy system), bottom-up (detailed representation of the energy system) and hybrid models (those that include the energy sector as a module), among which different methods (e.g., econometric, optimisation) are used. The distinction between bottom-up and top-down approaches is less conceptual and based more on the different sectoral and technological levels of detail [16]. The ESMs considered in this article are bottom-up models that consider the energy system in great detail.

In this article, the authors show why and how social science factors can be integrated into different types of ESM. For this purpose, an additional dimension is considered (micro and macro-perspective). The macro models examine the entire energy system in an aggregated form, while the micro models represent actions and decisions from the point-of-view of a specific sector or actors. For the category of macro models, both energy system optimisation (ESOM) (Section 2.1.1) and Computable General Equilibrium (CGE) models (Section 2.1.2) are described. In the micro-perspective, optimisation and simulation approaches are presented (Section 2.2). For each model category, the aim of the model, typical input and output data and representatives of the model are illustrated. Previous approaches to integrating empirical social science data into the models are shown in Section 2.3.

2.1. Techno-Economic Energy System Models from a Macro-Perspective

ESM with a macro-perspective depict the entire energy system, often including all sectors in great technical detail and consider both the operation and expansion of technologies in an aggregated form. They differ from models with a micro-perspective in that no individual decisions are represented, but the system (e.g., the whole of Germany) perspective is taken into account. ESMs with a macro-perspective can be divided into optimisation models and CGE models, which are described in the following two sections.

2.1.1. Energy System Optimisation Models

Energy system optimisation models (ESOM) depict the components of the energy system through technical and economic parameters. They usually make use of mathematical optimisation, whereby the costs for the operation and expansion of the system are minimised.

Model target: generation of a cost-optimal system composition under specified boundary conditions, such as a specified CO_2 reduction target. The technology expansion, the technology operation and the systemic interrelationship of the technologies are considered. Conversion technologies (electricity, heat and hydrogen), storage, imports and exports, as well as transmission networks, are considered. These can be applied to explore as examples the following questions: "Which system configuration enables a reduction in greenhouse gases by 95% by 2050 compared to 1990?", or "What effects will the transport sector have if the residential buildings are renovated?".

Typical input: electricity and heating demand, technology stocks, technology potential, techno-economic technology parameters, weather data, generation curves and energy source prices.

Output: technology expansion, technology operation, total system costs, CO_2 emissions.

Models: example representatives of the model category are: TIMES [17], REMod [18], ENERTILE [19], OSeMOSYS [20], Calliope [21] or MARKAL [22].

2.1.2. Computable General Equilibrium Model

A market equilibrium model or Computable General Equilibrium (CGE) model [23–26] focuses on the entire economic system and, especially, on the interrelations between sectors and countries [23]. CGE models are based on the neoclassical theory of general equilibrium, which consists of three equilibrium conditions, namely the zero-profit condition (no firm profits due to perfect competition), the market clearance condition (demand equals supply if prices are positive) and the budget constraint condition (household income must equal household expenses). Those equilibrium conditions are then combined with assumptions on agent behaviour and preferences (consumers and producers), mathematically formulated as a mixed complementarity problem and solved, such that a general equilibrium on all markets is identified. Technical details within the energy sectors are typically not considered; however, a hybrid approach allows the addition of some technical disaggregation.

The economic interrelations in a CGE model are represented through a circular flow of monetary units, where production factors are utilised for producing firms' output. From the provision of capital and labour, the consumers receive a money value (wage and return on capital), which they can either spend on the consumption of produced goods or invest. Investments increase the capital endowment in the subsequent period and, hence, increase production possibilities in the future. The government influences the optimal distribution of resources through taxes and benefits.

Mathematically, this circular economy is represented through production functions (profit maximisation of firms) and utility functions (utility maximisation of households). While the specification of different production functions allows the consideration of several technology options, technological changes and, hence, innovation, the specification of heterogeneous preferences captured in the utility functions enables the modeller to depict certain aspects of consumer behaviour.

Model target: cost-effectiveness analysis of energy and climate policy instruments considering the entire economic system.

Typical input: population growth, economic data for the base year (e.g., on production factors, technology efficiencies, etc.), development of CO_2 emissions.

Output: development of Gross Domestic Output (GDP), employment, international competitiveness, CO_2 prices, electricity generation, etc.

Models: example representatives of the model category are: DART [27,28], EMEC [29,30], GEM-E3 [31], IMACLIM-R [32], NEWAGE [33], PACE [34], SNOW-NO [35,36].

2.2. Techno-Economic Energy System Models from a Micro-Perspective

ESMs applied from the micro-perspective include a detailed technological representation of the system on individual aspects and incorporate, for example, investment behaviour. These models are often used to provide a rational basis for decisions on energy policy decisions and therefore act as decision support. These types of models operate either based on exploring the impact of specific policies on a particular energy demand sector (such as buildings, households, industry), or pathways to achieve certain objectives. Energy system models following a micro-perspective can be distinguished according to the underlying modelling approach that determines the type of dynamic representation of technology diffusion and energy demand development over time [37]. Thus, bottom-up energy system models can be categorised into simulation, optimisation and accounting models. Simulation models represent energy demand and energy supply descriptively [38], taking into account microeconomic decision-making and different drivers of technological diffusion. Accordingly, the design of simulation models aims at reproducing a given system—e.g., the building sector—and studying its development and transformation in the real world under different exogenous scenario variables. Optimisation models designed for representing a micro-perspective are based on the same framework as optimisation models on the macro-perspective described in Section 2.1.1. In contrast to simulation models, it follows a prescriptive approach. The goal is to derive different cost-optimal system states considering different market conditions and specific policy objectives. Applied on the micro-perspective, optimisation models can also be described as decentralised optimisation, which minimises the costs or maximises the utility of certain actors by focussing on the specific drivers for investment and consumption of the specific sector in question. The development of energy demands and technology uptake rates derived from simulation models can also be integrated as upper or lower boundaries for modelling technology diffusion with optimisation models. Therewith, a cost-effective pathway for a specific technology within the expected range of market uptake can be assessed. Accounting represents the third modelling approach in this category. The main difference between optimisation and simulation models is the exogenous choice of technology and market shares by the modelled user. Since technology diffusion is not explicitly modelled, accounting models are not within the scope of this paper.

Model target: uptake and distribution of particular technologies within a specific sector; simulation models aim at imitating the behaviour of real-world systems, whereas optimisation models focus on finding the best solutions.

Typical input: depending on the model type (simulation, optimisation), scope and level of detail, different inputs are required, e.g., techno-enviro-economic characterisation of existing and potential buildings and technologies, socio-economic characterisation for actors/investors, market shares, energy service demands (by end-use, energy carrier and/or specific technologies), energy prices, resource potential, availability of energy infrastructure.

Output: demand structures for the consumption and use of energy carriers and technologies, capex, opex, emissions, installed capacities, market shares.

Models: Invert/ee-lab for the buildings sector [37,39,40], TAM (TIMES Actors Model) [41–43], TAM-Households [42], Residential Sector Demand Module National of the Energy Modelling System (NEMS) [44,45], the Canadian Integrated Modelling System (CIMS) [46,47], REF-IF [48], FORECAST model [49], EnergyPLAN [50].

2.3. Literature Overview Considering Social Science Findings and Inclusion in Techno-Economic Models

In the following, literature considering social scientific findings and their inclusion into ESM is shown, following the categorisation of macro-perspective (ESOM and CGE) as well as micro-perspective energy system models.

2.3.1. Macro-Perspective

Energy system optimisation models: Few approaches combine social science approaches with optimising energy system models. One area is the consideration of context scenarios as in [51–53]. The approaches to scenario building differ between story and simulation (SAS) and CIB (cross-impact balance). SAS is a combination of narrative storylines and numerical simulation models. The CIB approach first evaluates the interactions between different scenario descriptors to then ensure a set of consistent parameters. The scenarios are composed partly of qualitative and quantitative descriptors. Some of these quantitative descriptors can be put directly into the model and serve as coupling descriptors [54].

A direct adaptation of an EMS was carried out in [9,55] to combine the aspects of local acceptance for wind turbines and grid expansion with the RenPassGIS! model. A similar approach was used in the 4Nemo project to integrate local acceptance factors in electricity market modelling [56]. In [8], acceptance of renewable energies was indirectly integrated into the ENERTILE model using intangible costs. The inclusion of social science findings into ESMs to include behavioural aspects to account for investment, consumption and preferences are explored, for example in [57].

Previously, the connection between technology genesis, knowledge, technological progress and market diffusion had already formed the basis for the further development of numerous energy system models. One or two-factor learning in different spatial contexts was discussed, e.g., by [58]. The main problem in the application is the requirement of a MILP format (mixed integer linear programming), which leads to increased computational times or drastic reductions in complexity.

Computable equilibrium models: Computable equilibrium models comprise the most commonly used methodology for cost-effectiveness analysis of energy and climate policy instruments. The literature shows approaches for model coupling between a general equilibrium and an energy system model as well as the inclusion of technological details in a CGE model framework. Refs. [16,59] present a hybrid modelling method for including technological details in a CGE model framework and show results for impacts of energy policies in the electricity market. A similar approach with a technologically disaggregated representation of the electricity sector in general equilibrium models is found in [25,60–62].

However, technological disaggregation is not limited to the electricity sector. Various studies focus on the disaggregated representation of the transport sector. These include [63–70]. In the building sector, the inclusion of technological details has not yet progressed as far, with the work of [71] being the most relevant.

Other CGE models also include a more or less detailed disaggregated representation of household energy demand. The SNOW-NO model [35] is a CGE model for Norway, which provides an empirically estimated marginal avoidance cost curve to represent energy efficiency investments in the building sector. It also contains approximate modelling of vehicles and energy sources used by households to produce their mobility services, and a similar approach for buildings and energy sources used to produce space heating services. However, the exact modelling is not further documented. A comparable technology model is contained in the EMEC model, which additionally distinguishes between different groups of households [29,30].

The GEM-E3 model adds durable goods on the consumption side in addition to general productive capital, to adequately take the demand for energy services from households into account by considering vehicle and heating types from a technology perspective. However, the documentation by [31] contains little information on the modelling and calibration process. The IMACLIM-R model for France [32] is one of the few known general equilibrium models that represent vehicles and buildings as durable consumer goods in the provision of the energy services for mobility and space heating by households. This is done in a separate module that transfers the respective initial endowment of production factors (including vehicles and buildings) from one period to the next. Ref. [26] combines most of the approaches presented and analyses the energy demand of private households in Germany and its significance for climate protection.

Model approaches that focus in particular on CGE modelling of energy efficiency improvements and technical progress can be found in [26,71,72]. Refs. [73–77] examine distributional aspects of climate policy with regard to households. Ref. [78] additionally addresses behavioural aspects. Model approaches that focus in particular on CGE modelling of energy efficiency improvements and technical progress can be found in [25,72,73]. Refs. [74–78] examine the distributional aspects of climate policy concerning households. Ref. [79] additionally addresses behavioural aspects.

2.3.2. Micro-Perspective

Findings from social science are applied in bottom-up energy sector models mainly to explicitly model investment decision behaviour and to identify non-economic barriers and stakeholder specific factors influencing the diffusion of technologies and technology choice. The different approaches in simulation models included (1) the integration of empirical research from discrete choice or conjoint experiments, (2) surveys based on socio-psychological theories and (3) representation of decision-making based on decision heuristics and bounded rationality [37]. Discrete choice analysis (DCA) is a widely used methodology for describing consumer decisions and quantifying decision variables [80]. Since energy sector simulation models often apply the logit-function to model market share distribution, the integration of empirical results from choice experiments are a natural choice. However, only a few studies have shown a direct link between the design and results of a choice experiment and an energy sector model. Within the European project CHEETAH, results from a DCE have been integrated into the Invert/ee-lab model [81].

Some approaches draw on socio-psychological theories to describe consumer behaviour and technology choice as a psychological process based on individual perception, habits and norms [82–84]. A theoretical framework for modelling the investment decision behaviour of residential building owners' technology diffusion of heating systems and efficiency measures, based on the Theory of Planned Behaviour (TPB), has been suggested by [85].

The third category is related to results from social science studies that question the assumption of rationality and describe the decision-making process as a series of different rules or heuristics that are applied depending on the decision situation and degree of information [86–88]. Integration of findings on bounded rationality heuristic decision-making as well as psychological behaviour theories and social interaction in energy sector simulation models can be realised by an agent-based modelling approach. Examples of agent-based modelling approaches explicitly integrating these findings in technology diffusion models are presented in [37,89,90].

Optimisation models aim to identify the least-cost solution to overarching objectives, and while some investment and other behavioural aspects have been included, the aim is not to reflect the behaviour of individuals, as is the case in simulation models. Ref. [56] highlights the most common ways behaviour has been included in micro-ESOMs to date, emphasising that behaviour is often limited to investment and consumption, reflected in models through disaggregation, and varying discount and hurdle rates—applied globally or towards specific sectors or technologies. Optimisation models aim to identify the least-cost solution to overarching objectives, and while some investment decisions and other behavioural aspects have been included, the aim is not to reflect the behaviour of individuals, as is the case in simulation models. Ref. [57] highlights the most common ways behaviour has been included in micro-ESOMs to date, emphasising that behaviour is often limited to investment and consumption, reflected in models through disaggregation, and varying discount and hurdle rates—applied globally or towards specific sectors or technologies.

2.3.3. Summary

In summary, the literature review shows that from the micro-perspective models, different approaches to integrating behaviour are already considered. From the macro-perspective ESOM and

CGE models, the level of technological detail is already being increased in some studies, so that a convergence between market behaviour and technology is taking place. In the areas of ESM from a macro-perspective, it becomes clear that too little attention has been paid to the social sciences, and only individual aspects have been focussed on, such as market distribution, local acceptance or scenarios based on context. This is mainly because the original purpose of the models was to find the cost-optimal solution for the energy system. In the future, however, social boundaries should also be considered in addition to the technical limits of the solution space.

3. Agent-Based Models to Study Technology Genesis and Policy Acceptance

There are social and behavioural factors that are determined by complex and dynamic interrelations between actors. In such cases, it can be beneficial to use dedicated agent-based models to simulate and analyse the underlying processes. In the following, two models will be presented, since these areas have hardly been used in energy system analysis up to now, but play an important role for transformation processes and will be taken up again in the following section.

3.1. Modelling Socio-Political Acceptance

The socio-political acceptance of political interventions (e.g., acceptance of regulations, taxes or subsidies, information campaigns) is one example of a social phenomenon that entails complex and dynamic interrelations between actors. Citizens are those who finally determine whether a policy intervention is accepted or not—however, there is a variety of actors who influence the public perception of policy interventions and interpret and frame the outcomes of public opinion formation (e.g., media, opinion leaders, lobby groups, political parties, etc. [91]).

Model target: in this domain, the goal is to simulate and analyse complex and dynamic relations between individual and collective actors that determine the emergence of socio-political acceptance for different kinds of policy interventions.

Typical input: simulation of social processes within society from different empirical sources, such as input from quantitative surveys (including choice and vignette-experiments as well as ego-centric network analyses), qualitative formats like interviews and focus groups, as well as information from public discourse (analyses of statements in social media, newspaper articles, press releases, etc.).

Output: information about the assertiveness of different policy options—linkable to techno-economic models as well as empirical analyses of issues outside the policy models' scope, identification of policy options that can have a strong impact on the overall CO_2 emissions (output of techno-economic models) and that will likely be well received by citizens (output of policy acceptance models) as well as by investors who actually decide about the uptake of sustainable technologies (output of additional empirical analyses).

Models: One approach to simulate and analyse such processes is currently under development; the PANDORA-model (**P**olicy **A**cceptа**N**ce, **D**iffusion of **O**pinions and **R**elations among **A**ctors).

3.2. Technology Genesis Model

Another example of a complex social phenomenon is knowledge generation and exchange, which is the basis for innovation and, thus, technological development and usability in energy systems [92–94]. Cooperation is key between actors like individuals, firms, organisations and networks [95], e.g., in research, education and production. Measures designed to strengthen knowledge-related processes in these areas cannot be captured by current energy systems modelling.

Model target: simulation of knowledge dynamics in innovation networks to assess the effects of financial, procedural and structural measures on innovation activities.

Typical input: data to calibrate the model concerning real actors in the field, including statistical and structural information of innovation networks as well as behaviour in terms of knowledge generation and exchange, as well as production processes on the micro-level. Typically, the input is gained from a mixed-methods approach including patent analysis, project collaboration analysis, publication analysis, expert workshops, qualitative interviews, and statistical data. Furthermore, revenue potentials or demand of technologies with specific characteristics are required, ideally as model inputs from ESM.

Output: typically represents numerous indicators of the innovation system, simulated based on the assumptions taken. Impacts of politics on innovation activity can be assessed by comparing these indicators with respective assumptions for a predefined focus, like measuring innovation dynamics. Multiple runs considering relevant variations in parameters for each set of assumptions and a specific analysis of the results lead to correlations, which can then be considered in energy system models.

Models: an approach to cover these aspects represents the agent-based Simulating Knowledge Dynamics in Innovation Networks (SKIN) model [96]. It has been adopted for lithium batteries as key energy technologies, resulting in the SKIN-Energy version. A more broadly applicable version is currently under development [97,98].

4. Consideration of Sociological and Behavioural Psychological Aspects in Energy System Models

As a result of an interdisciplinary discourse among energy system modellers, social scientists, psychologists, economists and political scientists, the following social science factors were identified that should be considered in ESM: investment behaviour, user behaviour, local acceptance, technology genesis and political framework conditions. In this section, these aspects are analysed under the criteria: (1) motivation for consideration in ESM, (2) empirical data collection and (3) methods/possibilities for integration in ESM (macro- and micro-perspective). The methods for integration are differentiated into direct model input, monetarisation and soft-linking with other models. Soft-linking means that no direct interface or model iterations are performed, but rather the model output of one model is translated into the model input of the ESM.

4.1. Technology Adoption: Investment Behaviour

Table 1 provides an overview on the market acceptance factors that should be considered in ESM from a macro and micro-perspective (Section 4.1.1), empirical methods for data acquisition (Section 4.1.2), as well as the methods for the integration of investment behaviour into ESM (Section 4.1.3). The table is not to be understood line by line. The connections between the aspects to be considered, data collection and model integration result from the explanations in the text.

Table 1. Overview of objectives, methods of empirical data inquiry and possibilities to integrate aspects of investment behaviour into energy system models (ESMs).

Objective	Measurement/Inquiry for Relevant Data	Integration into Energy System Models	
		Macro-Perspective	Micro-Perspective
Macro-perspective: Aggregated investment behaviour (future realistic market shares)	Quantitative: Surveys, discrete choice experiment (DCE), conjoint experiment latent class analysis (clustering)	Monetarisation: Intangible costs (willingness-to-pay, WTP)	Monetarisation: WTP/ Discount rate for technologies and actors, hurdle rates
Micro-Perspective: Actor type, individual utility, demographics, attitude, decision situation, multi-stakeholders decision etc.	Qualitative: Focus groups, interviews, participatory observation etc.	Direct Input: Upper and lower boundaries for technologies; Technology exclusion	Direct Input Decision criteria, (heuristics) weights, partial-utilities for decision criteria, technologies and actors, actor specific budget/time constraints
		Soft-linking: Technology diffusion model	Soft-linking: Technology diffusion model

4.1.1. Motivation

A key component of the active transformation of the energy system to a climate-neutral system is the actual deployment of novel, more efficient and environmentally-friendly technologies. Based on [99], market acceptance and, thus, the process of market adoption of an innovation is a form of social acceptance. Ref. [100] provides an overview of social science determinants that influence the investment decisions of private and corporate actors. According to economic theory, the investment behaviour of a consumer can be explained by an increased utility compared to the total cost of ownership (TCO) of the consumer product [101]. Besides the primary utility, e.g., the generated heat by heating technologies, the utility created by a product can also be increased or decreased by other influences, e.g., the reduction in CO_2 emissions (e.g., due to environmental consciousness) or the consumer's image. Thus, this additional utility is crucial to understand and to model the adoption of novel technologies, especially for private consumers. However, personal preferences concerning additional utilities can be diverse and are more difficult to establish than preferences relating to monetary attributes of an investment decision. Thus, they are currently more often neglected in techno-economic modelling [102]. Besides, the information sources available to the customer as well as the customer's capacity to gather and process this information (e.g., restricted due to a lack of time or competence) are crucial to understanding the perceived value of different technology options. From a micro-perspective, it is, therefore, useful to consider individual factors that influence the investment decision, such as individual utility, demographics, attitudes, decision situation as well as multi-stakeholder decisions; while, at the macro level, it is important to consider the result of individual decisions in an aggregated form, for example through possible realistic market shares.

4.1.2. Empirical Data

Investment behaviour such as choosing to invest in a renewable heating technology instead of another heating technology is often described by analysing the preference structure of people (e.g., [103]). Before using quantitative multivariate methods to analyse preferences, a crucial question is often what attributes (or characteristics) of a product or choice situation potentially influence these preferences. The selection of attributes for the preference analysis can be chosen from an ad-hoc collection compiled by researchers designing a quantitative analysis of preferences, or by a qualitative analysis based on (expert) interviews or focus groups with the population of interest (e.g., [104]). Employing the latter approach can provide the additional advantage of clarifying theoretical considerations for questionnaire design including the selection of certain attributes for *DCE*s to reduce the risk of failing to capture relevant aspects of decision-making. Quantitative results regarding preferences can be translated into monetary values by assessing the (marginal) willingness-to-pay (WTP). For established technologies on the markets, those values can be derived from revealed preferences through existing market purchase data (e.g., [105]). To measure the preferences regarding new technologies entering the market, experimental approaches based on stated preferences are often applied. In particular, methods like DCE, where the respondent chooses between different products with different levels of the same attributes, are often used [101]. The results for the preference characteristics can be evaluated individually as, e.g., in [106,107], or used in other models such as diffusion models, e.g., [108,109].

As preferences can be diverse, socio-economic and socio-demographic information as well as, for example, (environmental) attitude are often surveyed in questionnaires to identify clusters (e.g., [103]). To do so, quantitative methods like latent class analysis can be applied. In addition, qualitative methods, such as focus groups, participatory observation or interviews, can be used to get deeper insights into processes that underlie the formation of different preferences.

4.1.3. Model Integration

Macro-Perspective: The results of macro ESM provide an understanding of the technologies that could be used to realise a climate-neutral energy system. In ESM, the costs of the system are optimised and, at the same time, CO_2 reduction targets are set. This can lead to a result in which, for example, almost all heating systems are replaced with heat pumps and the majority of buildings have been renovated. However, the actual implementation of this is the result of individual heterogenous investment decisions of private and corporate actors. Individual investment decisions and their influencing factors such as attitude or subjective norm are not represented in macro-perspectives optimising ESM. Great differences in investment behaviour have been shown since there is usually no distinction made between investor groups and their demographics, personal variables such as attitude, norm, conviction and their decision-making behaviour [110]. This leads to a gap between the results from macro-perspective and micro-perspective models due to the differentiation in the definition of the optimum of the system vs. investment behaviour, which ultimately leads to different system designs. One possibility to reduce the gap between investment behaviour and techno-economic overall system optimisation is the use of intangible costs, which can be collected as WTP more in the context of DCE and, thus, allow direct consideration in the ESM. Another possibility to depict investment behaviour in the macro-perspective model is the use of time-resolved upper and lower expansion boundaries and technology exclusion. The basis for this can be the results of other models (such as technology diffusion models using agent-based simulation, discrete choice models, system dynamics or innovation diffusion models [102]) or the application of an S-curve according to the theory of innovation diffusion [111]. The integration of more realistic investment behaviour in ESOM may help to quantify the consequences for other sectors; for example, examining which CO_2 reduction requirements are shifted to the transport sector if insufficient energy renovation rates or reductions are achieved in the building sector. Employing a DCE and the simulation of the diffusion of alternative drive concepts based on a discrete choice model, it was possible to show that if fuel cell electric vehicles (FCEV) are available at the market, they will achieve certain market shares even if direct electric vehicles are the more cost-effective alternative [112]. In [53] it was, therefore, assumed that a certain proportion of FCEVs needs to be met by the ESM REMod to draw a more realistic future scenario. Ref. [113] takes an approach to soft-link a system dynamics diffusion model with TIMES to provide more realistic market shares for FCEV in the vehicle sector. Firstly, it was tested to adjust costs in the ESM, and secondly, to set market shares in the ESM, with the conclusion that the second approach is most useful. Other applications of this modelling approach have been made in modal split adjustments. The basis of the work of [114] is an agent-based model, while [115] builds on a GIS-based analysis. The two studies each link these pre-analyses with a TIMES model for Denmark and the region of Gauteng in South Africa, respectively.

These improvements are also included in CGE models, where the inclusion of technological details is state-of-the-art. As a result, upper and lower expansion boundaries and technology exclusion are possible modelling approaches for CGE models, too. Additionally, the specification of heterogenous preferences captured in the utility functions enables CGE modellers to depict certain aspects of consumer behaviour and attitude factors. Here, environmental, health or time-use factors represent possible variants as well as higher-level welfare concepts such as happiness, well-being or the economy for the common good. The more empirical knowledge about diffusion and investment processes is available, the more precise the assumptions can be made for ESOM or CGE. This concerns, in particular, investment cycles and technology choices.

Micro-Perspective: Technology adoption from the micro-perspective follows either the simulation or the optimisation methodology and takes into account the adoption pathways for different actors or actor groups. These differences in investment and consumption behaviour by different household categories have been described through the incorporation of behavioural economics [116]. Similarly, different discount rates or intangible costs can also be applied to specific actor groups within a model or sector to express the variation of purchasing and consumption behaviour [57,117]. Results from discrete choice models have also been applied to provide insights about the projections of technology adoption through, for example, discrete choice models [57,118]. The WTP in consumers has been addressed through disaggregation by income group to account for differences in consumption and affordability [42,117,119,120]. Efforts have been made to include non-technical influences on investment choices; for example, the true costs of modal shifts in the transport sector, which highlights the hidden costs of mode choice [121]. Different investment and consumption behaviour has also been reflected through disaggregation, where different groups or sub-sectors will be modelled with different energy demands, available technologies and discount rates [122–124]. In addition to disaggregation, discount and hurdle rates, the TAM-Households model also makes use of budget constraints to reflect variations in the investment and consumption behaviour of different actors depending on their socio-economic circumstances [42]. Budget and time constraints are factors influencing investment and consumption behaviour of various actors in the model, and have additionally been considered, particularly for households [42,125] and transport [41,126]. This caps the available budget for investment and/or consumption for specific actors and thereby provides the cost-optimal technology choices by a more diverse share of actors. Expressing time constraints reflects the individual's willingness to compromise on comfort towards more individualised or public solutions, i.e., cars or public transport.

4.2. Local Acceptance for Technologies

Table 2 gives an overview on the aspects that should be considered in techno-economic macro and micro-perspective energy system models concerning local acceptance (Section 4.2.1), how these aspects can be measured (Section 4.2.2) and how they can be integrated into ESM from the macro and micro-perspectives (Section 4.2.3).

Table 2. Overview of objectives, methods of empirical data inquiry and possibilities to integrate aspects of local acceptance into energy system models (ESMs).

Objective	Measurement/Inquiry for Relevant Data	Integration into Energy System Models	
		Macro-Perspective	**Micro-Perspective**
Macro-level: Local socially-accepted technology potential (saturation-level)	Quantitative: Survey, DCE, experimental and quasi-experimental field studies	Monetarisation: Intangible costs (willingness-to-accept)	Direct Input: User constraints (user-specific discount rates or market shares, hurdle rates, market shares)
Micro-level: Individual factors (not in my back yard, NIMBY), Local social factors, Socio-political factors	Qualitative: Focus groups, interviews, discourse analyses, participatory observation etc.	Direct Input: Regional upper and lower boundaries for technologies; Technology exclusion	Soft-linking: Micro model of local acceptance
		Soft-linking: Micro model of local acceptance	

4.2.1. Motivation

The specific design and speed of transformation of energy systems are strongly influenced by their social evaluation. Social evaluations are complex and, e.g., the authors of [99] propose to differentiate between socio-political acceptance, market acceptance and local acceptance. The focus of many empirical studies on conflicts and questions of acceptance of power system transformation is on local acceptance problems, for example, in grid expansion or the construction of new wind farms [127] or on the acceptance of CO_2 storage sites [128]. The corresponding research has mainly dealt with the NIMBY (not in my backyard) effect (e.g., [129,130]) and was guided by the assumption that the local evaluation and the overall social evaluation of a technology are often contradictory for "selfish" reasons. On an individual micro level, local acceptance is dependent on individual factors like attitudes, landscape aesthetics, additional costs (benefits), knowledge and trust. Yet, conflicting structures and issues of acceptance are anchored at many levels, and as a whole go far beyond local resistance [131]. More recent research points to the connection between political and social acceptance on the one hand, and local acceptance on the other. For example, local conflicts, which are often (too quickly) categorised as NIMBY, can turn out to be conflicts in which actors reject a transformation pathway that focuses exclusively on the expansion (and, thus, large land consumption) of renewable energies instead of focusing on electricity savings or energy efficiency measures [132]. Other research looks at local conflicts in detail and deals with matters of distributive justice, perceived procedural justice, etc. They address social factors that explain local acceptance. In any case, problems with acceptance can lead to certain technological options being eliminated or becoming significantly more expensive, thus having a major impact on the transformation process as they influence the local socially-accepted technology potential on a macro level.

4.2.2. Empirical Data

For the analysis of local acceptance of energy technologies, social science can draw on quantitative and qualitative methods. Quantitative methods such as surveys, quasi-experimental or experimental field studies and DCEs are suitable for analysing causal or correlational relationships between factors that inhibit or increase the acceptance of technology and the relative importance these factors play in decision-making. Data collected in this way can be integrated via direct interfaces into energy models, for example, when investigating to what extent an increase in distance regulation or the implementation of local citizen participation measures increases the acceptance of wind turbines [8]. At the same time, unravelling the complexities of these issues is not trivial. The use of questionnaires or surveys takes a lot of imagination or experience with a certain technology to be able to visualise what is meant by 100 m, 500 m, etc., and then give reliable information about ones' behaviour when confronted with such a hypothetical scenario. Doing so through means of experimental or quasi-experimental field studies is often more difficult and resource-intensive than applying survey or questionnaire methodologies, but also yields more reliable information about the actual behaviour of participants and the causal—instead of correlational—relationships between factors (e.g., [133]). Qualitative methods (focus groups, interviews, discourse analyses, participatory observation) are used to understand and explore acceptance problems rather than to causally investigate influencing factors. In these methods, text materials (documents, recorded observations, arguments recorded and transcribed during interviews or focus groups) are coded and interpreted by the researcher. Often, a combination of qualitative and quantitative methods is used in which knowledge from qualitative analyses is employed to design and plan quantitative methods. Interviews are often conducted first to gain a better understanding of the object of investigation and then, in a second step, a questionnaire, a DCE or a representative survey is designed.

4.2.3. Model Integration

Macro-Perspective: According to the results of cost-optimising ESOM, wind power plants and transmission grids, which face the majority of local acceptance problems [55], are central technologies in the future energy system [134]. Within the ESOM, the costs as well as the potentials, or so-called cost–potential curves, of the technologies are given as input. The model result is the cost-optimised expansion of the technologies and their regional distribution. This may result in a system where, on the one hand, the expansion burden is higher than socially acceptable and, on the other hand, some regions are more burdened than others because their techno-economic potential is highest. The protests and citizens' movements against wind power or transmission grids show that this assumption of cost-optimal distribution and expansion is biased. One could assume a theoretical saturation limit of technology acceptance. On the one hand, increasing costs or a decline in the annual installed capacity, which may arise if projects are not realised or are delayed due to protests or complaints, need to be taken into account if the expansion is above the saturation limit. On the other hand, the costs or additional technology capacity arising from participation or compensation measures would have to be taken into account to push the saturation point of technology acceptance upwards.

Possibilities to address the issue of local acceptance in energy system models from the macro-perspective are, for example, the consideration of intangible cost, quantified by willingness-to-accept [135]. The potential of technology can be reduced or local upper and lower limits can be set in the ESM to take into account the accepted technology saturation, which can be quantified based on empirical studies. This approach can also be applied for technology-based CGE models (see Section 2.3.2). It should be noted that "saturation" depends on personal factors such as attitudes and norms as well as regional conditions and is very heterogeneous. For technologies with considerable local acceptance problems, technology exclusion can also be implemented in the model. Another possibility is to soft-link with a model addressing local acceptance from a bottom-up perspective.

Examples for the integration of local acceptance in energy system models are shown in [9]. In the context of this work, the wind expansion in the electricity market model renpassG!S was optimised based on an empirically determined local burden level. In [55], the time delay of the transmission network expansion was determined with the same model. In [8], issues of local acceptance of renewable energies were integrated into the ENERTILE electricity market model via intangible costs. Ref. [53] considered aspects of the (un-)acceptance of major infrastructural changes (such as wind onshore expansion, transmission grids and overhead line trucks) in the energy system model REMod by limiting the potential of these technologies or excluding technologies (overhead line trucks).

Micro-Perspective: From the perspective of the investor, as designated in micro-perspective models, acceptance of technologies can be described through exogenously determining discount rates or market shares (i.e., user constraints), which can be applied to different investors or investor groups. Indirect factors that influence the local acceptance of technologies could also include parameters such as recommendations from technicians or relations, or information campaigns. The influence of these factors can be included in optimisation factors through the addition of a lower discount rate to reflect a lower hurdle to investment. Direct factors include defining specific market uptake shares for specific users, e.g., homeowners, through user constraints or profile-specific discount rates. These limits can also be set by soft-linking with a bottom-up model.

4.3. Behavioural Aspects Regarding Technology Use

Table 3 gives an overview on the aspects that should be considered in techno-economic macro and micro-perspective energy system models concerning user behaviour (Section 4.3.1), how these aspects can be measured (Section 4.3.2), and how they can be integrated into ESM from the macro and micro-perspectives (Section 4.3.3).

Table 3. Overview of objectives, methods of empirical data inquiry and possibilities to integrate behavioural aspects into energy system models (ESMs).

Objective	Measurement/Inquiry for Relevant Data	Integration into Energy System Models	
		Macro-Perspective	**Micro-Perspective**
Macro-perspective Consideration of realistic user patterns (regional differences, simultaneity)	Quantitative: Measurement, generic profiles, Surveys (willingness-to-pay, WTP; willingness-to-accept, WTA)	Soft-linking model coupling: Demand model	Soft model coupling: Demand model
Micro-Perspective Cluster (actor)-specific user behaviour, socio-demographics, attitude, norm, contextual/situational factors of behaviour, lifestyle		Monetarisation: Intangible costs (WTP, WTParticipate, WTA)	Direct Input Consumer-specific time series, Actor-specific preferences (willingness-to-pay, WTP; willingness-to-participate, WTParticipate; willingness-to-accept, WTA)
Macro and Micro-perspective Convertibility of consumer behavior (grid-friendly behaviour, rebound effect, sufficiency)		Direct Input: Model restrictions, Adaption of end energy demand, price elasticities	

4.3.1. Motivation

User behaviour determines the final energy demand and is, therefore, the starting point for energy system analyses. However, user behaviour is actor-specific and results from individual user behaviour (households/transport), but also industrial production and distribution as well as commercial trade and services. Within the integration of social sciences in ESM, two overarching factors play a special role: first, the inclusion of realistic demand profiles (temporal and regional). On a micro level, these are modelled with individual factors such as socio-demographics, attitudes, norms, lifestyle and also circumstances or context factors [136]. On a macro level, these factors are represented in aggregated form with realistic profiles. Second, the change of *user behaviour*, where aspects such as rebound effects, sufficiency, or grid-friendly behaviour play a role and where it is essential to identify factors and interventions that can effectively and reliably change behaviour (e.g., [137]). Of particular interest are aspects such as which technologies are used by whom and when, as well as the willingness-to-accept (WTA) or to adapt their demand according to, e.g., external controls of operation schedules for home storage systems or electrical vehicles to facilitate grid-friendly demand (e.g., [138]). This aspect becomes more relevant in a future energy system that is characterised by increasing shares of fluctuating renewable energy sources (e.g., [136]).

4.3.2. Empirical Data

User behaviour can be described by constructing individual user profiles. This can be done based on measuring loads resulting from a user interacting with an end-use technology or based on developing synthetic profiles from other sources on user behaviour such as time-use data (e.g., [139]) or more aggregate consumption data. Concerning household technologies, using measurement campaigns of technologies is often a resource-intensive research approach, but it has the advantage of measuring actual demand profiles as they occur in field settings. Depending on the research objective, user profiles can be applied individually or can be aggregated into generic profiles for different user groups. The profiles can have different temporal resolutions and can be measured over different periods. Ref. [105] collected and aggregated 415 individual hourly electricity loads of homeowners' consumption over 12 months. The resulting load profiles were utilised to evaluate the potential for photovoltaic and battery systems under consideration of seasonal effects. Such measured or synthetic profiles can be aggregated to a macro level to account for a region or user group by scaling with appropriate factors (e.g., number of users) and applying stochastic methods. Ref. [140] has modelled the fuel demand profiles for hydrogen vehicles based on the refuelling behaviour of conventional vehicles measured at two filling stations. For a general application of those profiles, a stochastic algorithm has been applied to the time series to receive more realistic profiles without repetitive patterns. Besides, quantitative survey approaches can also be employed to query user behaviour. Especially for novel technologies and the changing energy system, it can be an appropriate approach to describe to what extent users would be willing to adapt their current behaviour, e.g., with a monetarised approach to access the willingness-to-pay and accept (WTP, WTA), e.g., incentives for flexibility provision. For example, Ref. [141] surveyed German households to measure WTP and WTA regarding the security of supply.

4.3.3. Model Integration

Macro-Perspective: The temporal demand for final energy in households, transport, industry and commercial trade and services is the basis of the energy balance in energy system models, whose premise is to meet the demand, to shift it by flexibility options or to reduce it through efficiency measures. However, the availability of demand data is only given for partial areas. Therefore, *model coupling* with bottom-up demand simulation models such as MAED-2 [142], HERMES [143], SynPro [144,145] or Forecast [49] are often used to calculate heating or industrial loads depending on influencing parameters such as weather or GDP and different user behaviour. User behaviour also depends on other factors such as context, lifestyle, social milieu, attitudes, norms, demography, etc. Correlations between final energy demand over time and personal variables can only be considered in energy system models to a very limited extent and are usually covered through a separate demand simulation. The time horizon of energy system models has a long-term character (mostly 2050), so the change in temporal and absolute demand is an important model input [134].

Concerning flexibility, a key assumption in the ESM is the proportion of the population that accepts external controlling of technologies to ensure network service operation (Willingness-to-participate (WTParticipate), Willingness-to-accept (WTA)). This concerns technologies such as electric vehicles, PV home storage, heat pumps or other household appliances. This can be realised either with model restrictions, where, for example, 30% of the population makes the vehicle available for vehicle-to-grid and grid-to-vehicle applications, [146], or with intangible costs.

Another important aspect regarding energy demand is rebound effects of energy efficiency measures, which has been empirically demonstrated [147]. This effect can be implemented in energy system models through reduced demand (adaption of end energy demand). However, the exact quantification of the effect is subject to uncertainty and also depends on the efficiency measures in question [148]. So far, ESMs have often assumed a constant energy demand, taking into account energy efficiency measures.

The change in demand concerning prices can be quantified using price elasticities. According to [149], long-term elasticities are based on a change in the capital stock, whereas short-term elasticities are based on short-term consumer reactions, which in principle occur without a change in the capital stock. Long-term price elasticities in the energy sector, which are relevant for use in energy system models, are typically related to individual final energy carriers and their respective applications. For broader use of this approach, long-term price elasticities concerning different forms of energy service demands depicted in the models would have to be determined.

However, the importance of sufficiency in modelling is increasing [150]. Sufficient behaviour leads to a reduction in final energy demand. Based on empirical data or assumptions on final energy demand, absolute demand can be adapted, as shown in [53] in the sufficiency scenario.

Micro-Perspective: Variances in consumption behaviour included from the micro-perspective are typically defined through disaggregation of energy demands by the classified consumer groups as a reflection of the drivers of demand for that specific subgroup [116]. These demands can be projected into the future for each defined consumer based on assumptions for either the shift in the number of households in that group or by changing the demand figures based on adjustments in the demand profile (e.g., due to rebound through increased energy efficiency, increased demand from higher appliance use, decrease in demand due to energy efficiency, etc.) [119,123].

4.4. Technology Genesis

Table 4 gives an overview on the aspects that should be considered in techno-economic macro and micro energy system models concerning technology genesis, how these aspects can be measured and how they can be integrated into ESM from the macro and micro-perspectives.

Table 4. Overview of objectives, methods of empirical data inquiry and possibilities to integrate technology genesis into energy system models (ESMs).

Objective	Measurement/Inquiry for Relevant Data	Integration into Energy System Models	
		Macro-Perspective	**Micro-Perspective**
Macro-level: R&D developments, time of technology genesis	Model Economic micromodel, Technology genesis model	Direct Input Technology parameters, annual upper and lower boundaries for technologies	Direct Input Technology parameters, annual upper and lower boundaries for technologies
Micro-level: Political measures aiming at the (faster) development of new, innovative technologies, Knowledge processes	Quantitative: Statistical data (patent analysis, project collaboration analysis, publication analysis)	Soft-linking: Technology genesis model, economic micromodel (dynamic learning curves)	Soft-linking: Technology genesis model, economic micromodel (dynamic learning curves)
	Qualitative: Expert workshops, interviews etc.		

4.4.1. Motivation

The dynamics in the development of new technologies significantly influence the potential dynamic of meeting targets as well as the necessary composition of technologies in the energy system. This has a strong influence on results from energy systems analyses. The fundamental innovation processes driving technology development (R&D) are highly complex and non-linear [151]. Furthermore, they are characterised by a high number of systems involved, including systems of techniques, economics/markets, production, knowledge and social entities. Furthermore, implementing such technologies requires knowledge and educational management to enable society to deal with new technologies. From a macro-perspective, R&D developments should be considered in terms of techno-economic developments and the duration of the technology genesis. From a micro-perspective, it is important to include both knowledge processes and the impact of *policy measures* towards new innovative technologies.

4.4.2. Empirical Data

One possibility to integrate innovation into ESM is the integration of dynamic learning curves (e.g., [152]). These are outputs of economic micromodels. Another possibility is the (soft) linking with technology genesis agent-based models, as described in Section 3.2. Such genesis models can be calibrated on two levels: on a micro-level of individual behaviour and characteristics of the agents and on a meso level according to the macroscopic empirical occurrence of innovation structures. To get as much information as possible about innovation dynamics in a sector, often mixed-methods approaches are applied. While micro behaviour can be implemented in genesis models via algorithms reflecting findings in the literature about processes of research, development, production, collaboration, and knowledge exchange, statistical data and data of cooperation are needed to characterise agent-types and to try to reproduce observed constellations in innovation networks. Additionally, interviews and expert workshops can be used to focus on questions relevant in practice and to configure the model most realistically. Moreover, the model behaviour and results are compared to real circumstances concerning impacts of measures via what-if experiments and typical innovation dynamics [153,154]. Furthermore, revenue potentials or demand for technologies with specific characteristics is required, ideally as a model input from ESM.

4.4.3. Model Integration

Macro-Perspective: Innovation and innovation processes form the basis of the availability of technology and its techno-economic performance, but also the provision and adequate processing and transfer of knowledge about this technology and its applicability. This plays a decisive role in energy system models since innovative technologies and further developments of existing technologies are set as model inputs. Knowledge about innovation processes for individual technologies, such as large heat pumps, direct air capture of CO_2 or Carnot batteries, enables this to be taken into account in the energy system model in an appropriate form. The knowledge about innovation and knowledge diffusion can be quantified by empirical work or implemented by direct model integration or model coupling with technology genesis models [155]. Concerning direct model integration, CGE models typically include knowledge as an additional factor in the production factor [25,156].

Agent-based models can be applied to assess the influence of knowledge generation and flows on innovation dynamics [97,98]. A soft-linking of such models with energy system models allows the consideration of measures orientated around knowledge and education aimed at new technologies to foster the energy transition. Output parameters that can be used in ESM for different measures and framework conditions include changes in the time of knowledge diffusion and technology availability, and the associated costs.

Micro-Perspective: From the micro-perspective, innovative technologies are considered in models through their availability to the actor groups at a certain point in time when they come on the market. These technologies will be taken up in optimisation models through their cost-competitiveness.

Empirical studies have shown that the role of intermediaries (such as technicians, handyman) plays a major role in technology adaptation [157,158]. They are often not broadly trained to provide adequate advice to the potential adopters of innovative technologies like heat pumps. There is the possibility of coupling a techno-economic bottom-up model such as Invert/eeLab with a technology genesis model such as SKIN to map the influence of knowledge transfer in the field of intermediaries and thereby do justice to the inclusion of knowledge dissemination.

4.5. Socio-Political Framework Conditions

Table 5 provides an overview on the aspects that should be considered in techno-economic macro and micro energy system models concerning socio-political acceptance (Section 4.5.1), how these aspects can be measured (Section 4.5.2) and how they can be integrated into ESM from the macro and micro-perspectives (Section 4.5.3).

Table 5. Overview of objectives, methods of empirical data inquiry and possibilities to integrate socio-political acceptance into energy system models (ESMs).

Objective	Measurement/Inquiry for Relevant Data	Integration into Energy System Models	
		Macro-Perspective	**Micro-Perspective**
Micro and Macro level Political strategy (measures) for existing technologies	Quantitative: Laws, Surveys, DCE, Vignette-experiments, ego-centric network analysis, etc.	Direct Input Measures as Hard constraints: bans, standards, new construction, standards, compulsory connection, incentives	Direct Input Measures as Hard constraints: bans, standards, laws, new construction, standards, compulsory connection, incentives
Micro-level Socio-political acceptance	Qualitative: Interviews, focus groups, web-scraping, natural language processing, etc.	Direct Input Context scenarios	Direct Input Context scenarios
	Model: Socio-political acceptance model	Soft-linking Socio-political acceptance model	Soft-linking Socio-political acceptance model

4.5.1. Motivation

Energy system models can account for different socio-political framework scenarios by assuming different learning curves and cost degressions over time (e.g., to account for the dynamics of technology development) or other technology parameters (e.g., to account for a change in the public perception of technology) as well as by defining model restrictions (e.g., to account for binding regulations like technology bans). With such approaches, it is possible to estimate the range of different dynamics in the transformation of the energy system, depending on different socio-political conditions. Besides, such approaches make it possible to estimate the range of different dynamics in the transformation of the energy system depending on different socio-political conditions. However, it remains undetermined how realistic the occurrence of different socio-political scenarios is or how policy measures should be designed to be effective and efficient. The combination of energy system models with analyses that provide insights into such questions would be of great practical importance.

4.5.2. Empirical Data

There are several approaches for empirical analyses of the socio-political framework conditions. These include different forms of quantitative surveys (e.g., direct measurement by Likert- and rating-scales, discrete-choice- and vignette-experiments or ego-centric network analyses) as well as qualitative approaches (e.g., interviews and focus groups) of the public opinion regarding different political courses of action [91]. In addition, there are also methods to analyse public discourse regarding different political options. These include qualitative or quantitative (e.g., by web-scraping and natural language processing and/or network analyses) content analyses of political documents, news in media portals or comments in social-media (see e.g., [159–163]).

4.5.3. Model Integration

Macro-Perspective*:* The political framework and its development play a significant role in energy system models. Although ESOMs cannot directly, or can only partially, reflect the effects of single policy measures, they are considered implicitly, as they influence several model parameters. Regulatory measures can be taken into account in ESM by excluding certain technologies, or by making certain assumptions such as "everyone is obliged to provide their electric vehicle for grid stabilisation". Investment incentives can be implemented by changing cost assumptions. Standards can be adopted through technical parameterisation. The realisability of different framework conditions is related to socio-political acceptance [91]. Socio-political acceptance can be determined by agent-based models based on empirical surveys. As a result, information about the feasibility of different policy measures can help to develop a well-founded scenario framework. The political framework conditions are also often bundled into so-called policy packages. One way of putting together consistent policy packages is the cross-impact balance analysis, which quantifies the mutual interactions of various determinants so that only plausible and consistent combinations of determinants (e.g., political framework conditions) can be chosen.

Micro-Perspective: Policy instruments have also been assessed in micro optimising energy system models to incorporate consideration for targets, requirements for laws, boundaries from regulations as well as incentives [164]. These reflect overarching targets, such as renewable or energy efficiency targets, defined directly through minimum or maximum capacity bounds. Additionally, taxes, such as carbon taxes, can be placed on the consumption of carbon-emitting fuels and the impact on specific actor groups analysed. Policy parameters related to acceptance can be included, as previously stated in Section 4.2.3, through the use of hurdle rates to encourage technology adoption. In micro simulation models, policy measures can be directly integrated, similarly to macro models, concerning standards, bans, incentives, etc. The difference to macro-perspective models is that the effect of the policy measure is endogenously quantified in market shares. This can be utilised by adding a choice attribute into a DCE and gaining utility values for regulatory, financial or nudging measures. Scenario variations can also be applied to evaluate the impacts of certain policies. The feasibility of measures can be implemented as soft-coupling with a socio-political acceptance model to create a valid scenario framework.

5. Concept of Model Coupling

Energy system analyses provide a basis for decision-makers regarding the design of and appropriate policy framework for the energy system. As described in Section 2, there are different approaches and models that assess different questions. The previous section has shown how empirical results and factors from the social sciences can be translated into macro and micro-perspective energy system models. However, it is not—or only barely—possible to develop a single model that takes into account all facets of the energy system, including the social environment. Based on an interdisciplinary discourse, this section suggests how the various models discussed can be coupled with each other to gain a deep understanding of the systemic interrelationships of the energy system and the transformation of the energy system. Figure 2 shows the concept of model coupling. Common to all models is that a context scenario must be defined initially to be able to show which effects arise under certain scenario conditions.

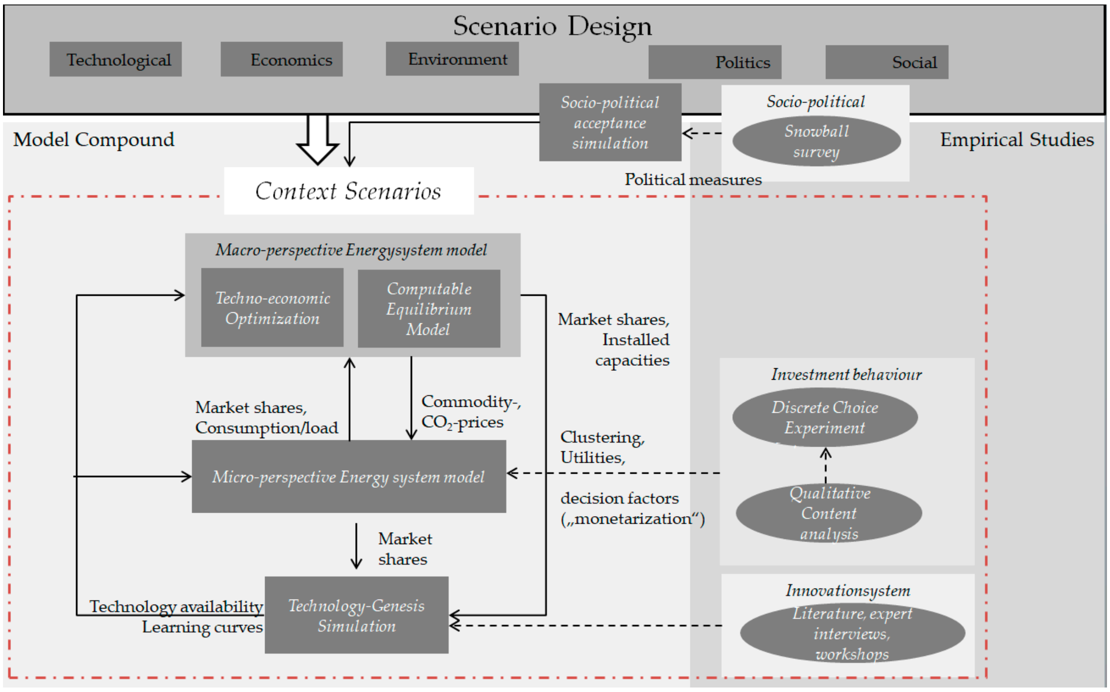

Figure 2. Schematic overview of possible interactions of the energy system model (macro-perspective), transformation path model (micro-perspective), technology genesis model (innovation) and socio-political acceptance model.

The scenarios are composed of various factors from different dimensions, which can be orientated to the social, technical, economic, environmental and political (STEEP) dimensions. When creating scenarios, the mutual influence of the scenario determinants and the resulting potential inconsistency must be taken into account. One approach to address this shortcoming and develop consistent scenarios is the cross-impact balance analysis [54].

If an entire model's compound is considered, as shown in Figure 1, it is helpful to first define a common scenario to provide the framework. It is useful to select determinants that overlap in the different models. Thus, the technological and economic assumptions on price developments, cost developments, lifetimes or efficiencies should be harmonised and possible corridors should be determined. Concerning the policy framework, possible measures should be identified that have to be considered within the models. One aspect is the socio-political acceptance by citizens of these measures influencing the feasibility of the measures and their probability of implementation. Empirical input regarding socio-political acceptance can be gathered through surveys and other quantitative and qualitative methods. By combining these inputs into an agent-based simulation, the feasibility of different policy frameworks can be analysed and used as input for soft-linking with macro- and micro models (Section 3.1). In addition, common determinants of social dimensions, such as GDP, population development, but also sufficient behaviour or environmental awareness, should be taken into account. About environmental determinants, factors such as air quality or availability of resources can be taken into account. In the context of this article, however, the social factors are the main focus.

The model coupling approach to be applied in this study combines the previously mentioned aspects and the energy transition with regard to heating.

Technological innovation or genesis is the basis for the technological field of transformation processes, such as the energy transition. The political framework sets the conditions, as focused technology research can be carried out, such as the German government's energy research programme or the European Union's Strategic Energy Technology (SET) Plan. Through targeted research and information campaigns, specific technologies are promoted to various actors. In addition to the technology genesis, the diffusion of knowledge is an important driver for the actual establishment of the technology in the market. This includes manufacturers, but also technicians and handymen, who influence the investment decisions of individuals. For the parameterisation of the technology genesis model, empirical studies (interviews, workshops, experts, etc.) are necessary to characterise processes and agents and to calibrate the model to observed innovation network structures, but also possible future market shares of the technology. As a result, an innovation model provides information on the temporal availability and shape of learning curves of technologies, which serve as input in ESM and diffusion models. Furthermore, the assessed amount of knowledge about innovative technologies of installers and craftsmen can be used to improve the modelling of technology diffusion.

Market acceptance or technology diffusion can be simulated or optimised based on micro-perspective energy system models. DCEs are a useful empirical data collection tool, in addition to the literature, as these can map the investment behaviour within an experiment and determine utility values based on which decision model can be built that is also linked to a stock model. The result of the micro-perspective model is the market penetration of technologies like heating systems, shares of heating systems and renovation rates based on investment behaviour under certain conditions.

If the target system is considered without taking investment behaviour into account, most ESM models conclude that heat pumps, as well as grid-bound heat supply with the simultaneous rising of the energy standard, are the solution in the transformation of the heat sector. A look at investment behaviour, however, shows that the majority of investments are made in gas condensing boilers, partly because of decision-making patterns and intermediaries such as technicians and the resulting investment decisions can also be implicitly reflected in the ESM. This makes it possible to quantify the effects of the framework conditions, e.g., in the building sector, on other sectors or imports of electricity or synthetic energy sources. In turn, the coupling is also possible in the other direction: Which basic conditions must be given (evaluation using a micro-perspective model) to reach a future target system.

It should be noted that with this type of model coupling, there is no successive model sequence presented. Instead, knowledge from the different models and their results, as well as the findings of empirical surveys, is made usable by improving the model assumptions of the individual models or the models themselves and by creating interfaces between the models. A common scenario framework is a basis for this. An interdisciplinary discourse clarifies the potentials and possibilities of model coupling. Overall, the analysis on a specific topic, such as the heat transition, can be significantly enriched by using different models and taking into account findings from different areas of transformation.

6. Discussion and Conclusions

Energy system models (ESMs) can serve as decision support tool to inform political decision-makers about the energy transition. Classically, ESMs optimise the system under cost-minimising criteria considering techno-economic parameters, simulate future demand or technology uptake, or use the methodology of equilibrium models. However, the transformation of the energy system to meet climate policy goals and the Paris Accord is a societal process that will not take place as at a cost optimum.

For this reason, an increasing number of studies have been aiming to include social sciences in energy system models. This article reviews these various studies to ascertain which aspects are included in energy system models and how this is accomplished. The review has shown that there is little consensus on which social science factors should be considered and how these can be instrumentalised. Therefore, as a result of an interdisciplinary discourse, this article shows which factors should be considered, how they can be collected and what theoretical possibilities exist to integrate them into ESM. For this purpose, a subdivision of ESM into macro and micro-perspectives was carried out. While the macro-perspective covers the entire energy system, the micro-perspective focuses on techno-economic models that reflect the diffusion of technology. The literature review on the integration of social science factors shows that, up to now, the focus has been on considering only single areas of the social sciences in ESM, such as acceptance or user behaviour.

The following factors were identified: investment behaviour (market acceptance), user behaviour, local acceptance, technology genesis and socio-political acceptance. The empirical methods range from qualitative methods like interviews or focus groups to quantitative ones like discrete choice experiments (DCE) or egocentric network analysis. In the area of integrating social science factors, various options emerge: direct model input via setting upper and lower limits or technology exclusion, and monetisation collected through DCEs, expressed as willingness-to-pay or a soft model coupling. For almost all questions in the context of transformation, findings can be generated through sub-models. Their results can, in turn, be used to feed into ESM. In particular, the areas of technology genesis and socio-political acceptance have so far received little attention in ESM, or their assumptions in ESM are usually not well-founded. Therefore, sub-models are typically employed to analyse these aspects.

For a single model, considering all the aspects discussed, the inherent complexity of such a model would prevent efficient modelling. Therefore, a model compound would be better placed to harmonise the integration of these various areas. A possibility for this was proposed in Section 5, in which coupling between energy system modelling from macro-perspective and microsystem models, in combination with agent-based models with a focus on technology genesis and socio-political acceptance, was presented. To ensure a coherent scenario analysis, the modelling group should define a scenario framework in the form of context scenarios in advance.

In summary, there is a great need to integrate social and individual processes in energy system models to achieve more realistic analyses. However, the social processes are sometimes very complex and only a simplified representation is possible. The article shows how individual points can be addressed, but there is still a great need for interdisciplinary cooperation to make the models and the analysis better and the findings more profound.

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