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Simulation versus Optimisation: Theoretical Positions in Energy System Modelling

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Abstract: In recent years, several tools and models have been developed and used for the design and analysis of future national energy systems. Many of these models focus on the integration of various renewable energy resources and the transformation of existing fossil-based energy systems into future sustainable energy systems. The models are diverse and often end up with different results and recommendations. This paper analyses this diversity of models and their implicit or explicit theoretical backgrounds. In particular, two archetypes are defined and compared. On the one hand, the prescriptive investment optimisation or optimal solutions approach. On the other hand the analytical simulation or alternatives assessment approach. Awareness of the dissimilar theoretical assumption behind the models clarifies differences between the models, explains dissimilarities in results, and provides a theoretical and methodological foundation for understanding and interpreting results from the two archetypes.

Keywords: energy system analysis; investment optimisation models; simulations models; modelling theory; renewable energy

1. Introduction

Climate change is forcing global society to change the energy system away from use of fossil fuels [1]. The design of future national renewable and sustainable energy strategies calls for energy system analysis models able to model the complex interdependencies and temporal characteristics of such. In the scientific literature most papers have focused on the quantitative aspects of these models and methodologies while less attention has been devoted to the social science and more qualitative issues of the design of sustainable energy strategies [2]. The purpose of this paper is to analyse the role of energy system modelling in the transition away from fossil fuels in democratic societies. Two important classes of models are presented, and their relation to politics, planning and rationality analysed and discussed. The basic points are illustrated with examples from the Danish energy transition debate, which has been going on since the 1970s.

The argument in this paper links to a central theme in Science, Technology and Society studies where in situations of techno-scientific controversy it is seen as a principal quality to have public involvement in such matters (cf. Callon et al. [3], Marres [4]).

The main purpose of energy systems modelling is to assist in the design, planning and implementation of future energy systems. Constructing a model inevitably means identifying and highlighting certain parts of reality in order to focus on the most important aspects in relation to one's specific purpose. Choices must be made about the sectors, technologies, and connections to include and exclude. This means that one can neither understand nor validate a model without understanding the theoretical background of the model—which in itself can be considered a theory of the modelled system—in relation to the specific context within which it was built [5,6].

Importantly, the construction of models is only part of the process since many choices are made beyond the modelling itself. First of all, it is necessary to define the purpose. Different purposes lead to different model designs and choices about data and other inputs. Other important parts are carried out during or after the modelling phase. Data must be gathered, results interpreted, and conclusions drawn. A further task is to design implementation strategies or even policy changes on the basis of the modelling results.

Many energy models have been developed that differ in various respects [7–9]. Firstly, origins are different. Some are sponsored by private organisations and companies [10], others by public authorities on various levels. Some are produced by the United Nations (UN) or large non-governmental organisation (e.g., IEA-WEO 2010 [11]), and some are made by independent research institutions. Secondly, models are different in terms of scale. Some have a national approach [12], others focus on regional levels [13], whereas some are designed to guide leaders in industry [14–16]. Thirdly, some models are of a general nature, whereas others focus on specific aspects such as, e.g., forecasting [17], buildings [18], shift towards distributed generation [19] or the inclusion of other sectors such as desalination [20]. In some situations a specific model has formed the basis for a dialogue between different parties [21], while in other cases a specific model has been criticized for being biased towards certain solutions and technologies [22] or infrastructures [23].

This variety makes it impossible to compare all kinds of models directly; it is necessary to focus on a limited set of comparable models. This paper is mainly concerned with energy system analysis models, which are meant for the analysis of future sustainable energy solutions at the national level.

Models used for such purpose have to address the following three key concerns:

- How to model a complete national energy system.
- How to model a radical technological transformation from the current system into a sustainable energy system.
- How to model the interaction between a national system and the surroundings in terms of e.g., exchange of electricity and biomass.

The focus in this article is on two classes of models, which in this paper will be presented as separate archetypes, even though they sometimes overlap and even though hybrids also exist. These are endogenous investment optimisation models and exogenous investment optimisation models. In the former, typically economically optimal investment strategies are determined inside the model whereas the latter is applied to simulate user-specified systems, and decisions on systems composition are taken outside the model. Investment optimisation is thus exogenous to the model. Endogenous investment optimisation models include Homer [24,25], Markal [21,26] and Balmorel [27]. Exogenous investment optimisation models include models like EnergyPLAN [28,29] and energyPRO. These two classes of models are detailed further in Section 2 including their mathematical design. In the remainder of the article, we shall refer to the two classes of models—or modelling approaches—as optimisation models and simulation models.

Other kinds of approaches exist. For instance, in exergo-economics [30,31] and emergy [32,33] attempts are made to combine thermodynamic optimisation with economics and hybrid simulation/investment optimisation models are also available such as The International Energy Agency's energy technologies perspective (ETP) model [34] which is based on TIMES MARKAL. Proposals have also been put forward to design transparent models suitable to enable interdisciplinary participation and/or similar approaches [35,36].

In this paper, the two classes of models are presented based on their key differences in terms of purpose and overall design. Afterwards, the implicit assumptions about the relationship between modelling and politics are analysed using various examples. Thirdly, the role of researchers and planners in the approaches is explored, followed by an analysis of the concepts of rationality in the two approaches. This is illustrated further with a few examples, before the conclusion is reached.

2. Simulation versus Optimization Modelling

A simulation model can be defined as a representation of a system used to simulate and envisage the behaviour of the system under a given set of conditions [37]. The term *optimization* is typically used synonymously with a modelling approach where a number of decision-variables are computed that minimize or maximize an objective function subject to constraints. These decision variables are typically energy system design characteristics.

An important difference is that simulation models only intend to envisage the performance of a given system, given certain assumptions, whereas optimisation models are searching for the optimal system design.

In real life modelling, one can easily find examples of optimization models used to identify different scenarios, which are then analysed more qualitatively. Similarly, simulation models may also be integrated into energy system optimisation systems [37–39]. Another example is Mahbub et al. [40] that combine investment optimisation and energy system simulation through genetic algorithms and simulation modelling, thus bridging the gap. Still, as presented later, the principle understanding of the implicit theoretical background provides valuable information on approaches.

Wurbs et al. [37] use a cognate distinction between prescriptive and descriptive models. *Descriptive* models are designed to demonstrate what will happen in terms of certain selected key parameters, if a specified plan is adopted, whereas *prescriptive* models seek to generate the plan that best satisfy the selected decision criteria. This is not an optimal terminology in this case, though. The models are not really descriptive in the ordinary use of this term, but should rather be called analytical: a series of key parameters are selected in advance and used to assess system behaviour. This inevitably involves a normative element as there, following Kuhn's paradigms, is no neutral expertise: choosing parameters means making judgments about the relative importance of selected issues—without necessarily making an exact ranking of these issues.

2.1. The Optimisation Approach

Mathematically, endogenous investment optimisation models may be established in various ways using e.g., linear programming, mixed integer linear programming and non-linear programming (see [41] for a comparison of these three approaches). These three are characterised by having an objective function, which is optimised numerically within a set of constraints.

The basic aim is to identify the optimal solution. Depending on the objective function, this may be in terms of e.g., energy consumption or environmental consequences, particularly CO_2-emissions, however most typically it is in economic terms. The choice of objective has significant impact on the result [42] in terms of optimal energy system design, however we will base our article on the common economic optimisation.

Thus, the optimal solution is typically either the least costly way of reaching a specific goal (the cost-effectiveness approach) or the optimal balance of economic costs and benefits (the cost-benefit approach). It is assumed that there is such a thing as the optimal solution, for instance an optimal investment strategy for a given country. This approach is illustrated in Figure 1.

In order to identify the least cost way from the current system into an optimal future system the description of the current system becomes essential. Typically optimisation models will have the current system as a starting point for the algorithms to identify the optimal way ahead. Therefore, it is typical for such models to concentrate on being very detailed and as accurate as possible in the description of the current energy system. And for the same reason they are well-suited for forecasting rather than backcasting.

From a theoretical point of view, this understanding is often closely related to neoclassical economic theory, where the optimal course results in the highest surplus, typically achieved through market mechanisms—supplemented with proper regulation in cases of market failures. Proper regulation here means in accordance with the results of virtual or imitated market behaviour, when real market results are unavailable.

Despite a number of practical challenges related to collecting data and developing algorithms, the idea remains that, in principle, one optimal solution exists and can be identified, if inputs are correct and sufficiently comprehensive, and the objective function is accurate. Uncertainties related to elements such as technological innovation or future fuel price fluctuations are typically considered as matters of risk and uncertainties that can be dealt with in quantitative risk assessments and sensitivity analyses.

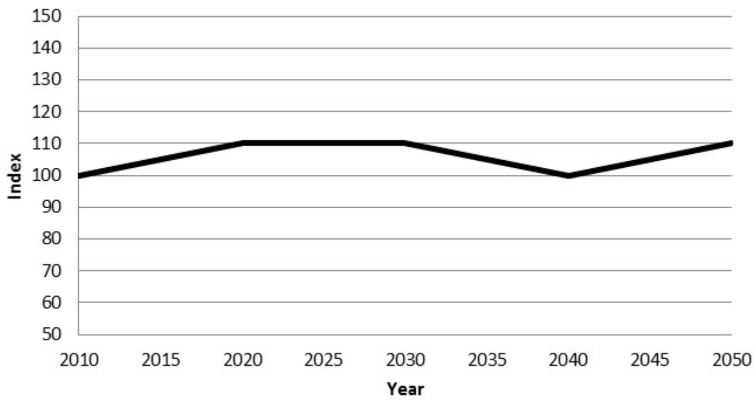

Figure 1. Simple illustration of the optimisation approach. It is assumed that one optimal solution exists. The purpose of the model is to identify this solution. The figure shows the development in just one key parameter, which could be a variety of metrics such as gross energy consumption, biomass demand, or district heating penetration.

2.2. The Simulation Approach

Mathematically, the same approaches may be applied for simulation models as for optimisation models, though without installed capacities as decision parameters. Other approaches are also frequently encountered. The mentioned EnergyPLAN is based on what the creators denote "analytical programming" to indicate an approach where rather than having a solver indiscriminatingly search through a space of possible decision values, the programmer has a priori established priorities and appropriate system responses to given impetuses. While the term "analytical programming" is found in the literature, its application within systems analyses and more specifically energy systems is not well-defined, and the term is usually used as a descriptor for EnergyPLAN. Another approach is found in energyPRO which is based on individual hourly priorities for energy units for a year and subsequent dispatch according to the priorities with a loop to check whether new productions interfere with previously established unit commitments (see [43]).

Several simulation models work on a national scale such as the EnergyPLAN model [28,29], but they are also used in relation to specific subjects such as district heating [44,45], building design [46], and policy design in the electricity sector [47]. Here the focus will be on the national level.

In simulation models the purpose is to analyse and compare options and/or scenarios that differ in relation to various key parameters such as costs, emissions, energy supply, and others. Simulation models may therefore also considered a type of scenario model. The basic assumption is that rather than establishing an optimal strategy based purely on quantitative analyses according to one criterion, scenarios are compared according to several criteria. Several relevant considerations need to be taken into account, and their relative importance cannot necessarily be measured by one common denominator. Consequently, several alternative routes and end states with dissimilar strengths and weaknesses ought to be identified and discussed. Such strategy is illustrated in Figure 2.

Using such approach the details of the current system becomes of less importance, while he details of the many options of the future become essential. Therefore, simulation models are typically more detailed in modelling of future technologies and energy systems rather than going into details with the current system. For the same reason the models are well-suited for backcasting.

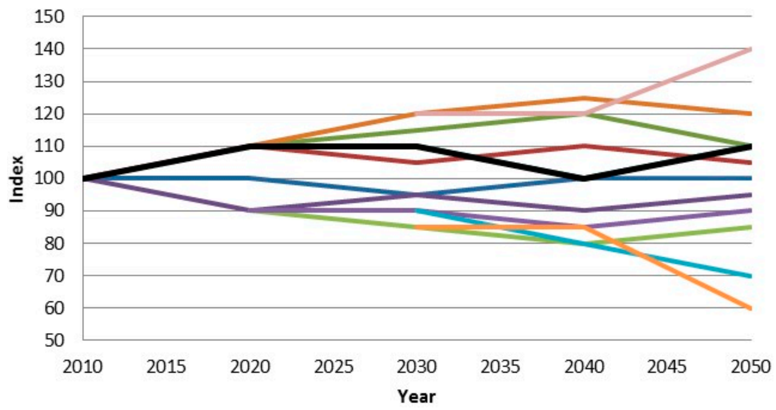

Figure 2. Simple illustration of the simulation approach. It is assumed that different future options have dissimilar strengths and weaknesses. The purpose of the model is to map the available options. The figure shows the various developments that may occur in a single parameter, depending on choices and circumstances. The parameter could be a variety of metrics such as the amount of biomass in the energy system.

From a theoretical point of view, this conception is cognate to institutional economics, which underline how markets rely on human-made institutional constructions influencing the very definition of economic optimality [48,49]. This point challenges the belief that one optimal allocation of resources should be identified and implemented under the conditions of a pre-defined market.

Simulation modellers need to be aware of the major uncertainties in relation to key assumptions such as future technological options, fuel prices, and political reactions. The very presence of such major uncertainties indicates the need to compare different solutions based on diverse assumptions. Similarly, the recognition that all market values ultimately depend on political choices is likely to create scepticism towards the conception of optimality.

2.3. Key Differences

The most important difference between the two classes of models lies in the crucial assumption whether the model itself can identify the one optimal solution or not. Optimisation models are expected to be able to make all optimisation decisions on the basis of a, typically standardised, set of restrictions, rules and presumptions in combination with a limited set of pre-defined gauges such as economic value. Conversely, simulation models leave it to the user to make all crucial decisions on the basis of a variety of considerations, which cannot be rated on the basis of one common denominator. Therefore, the considerations are comparable, but not directly commensurable (cf. Bernstein [50]).

In the optimisation approach, the modeller delivers information in the form of data, objective function and boundaries and leaves it to the model to identify the optimal solution on the basis of predefined goals. In the simulation approach, the user identifies a variety of potential system elements and uses the model to calculate consequences of different combinations in order to establish grounds for decision-making. The two approaches also tend to handle risks and uncertainties diversely. Optimisation typically aligns with quantitative-oriented risk assessment and sensitivity analysis, whereas simulation tends to align better with more qualitatively-oriented alternatives assessment approaches [51].

If the model is expected to optimize the energy system in relation to one specific parameter, typically economic value, all elements need to be specified in relation to this parameter. If, on the other hand, various parameters are at stake, the output of the model must be expressed terms of these. A weighing of parameters is possible—as in some Multi Criteria Decision Analysis approaches—however any normalisation and weighing of incommensurable parameters is to a high degree influenced by preferences. The generation of Pareto-fronts is another way to capture more criteria as in Mahbub et al. [40].

Computational time is a potential issue, however this is not so much a consequence of whether dealing with optimisation models or simulation models but rather the approach. In a comparison of computational time requirements for a dispatch model of 18 thermal power plants and a variety of boilers, heat pumps and thermal energy storage, linear programming had the lowest computational time [41]. Mixed integer had a roughly twice a long computational time and the non-linear programming approach was 4200 times slower when analysing the dispatch problem with a rolling 12 h foresight over a one month period, giving computational times ranging from 12 s to 14 h. With perfect foresight, computational times were "long" for the two latter approaches.

For comparison, EnergyPLAN—based on its endogenously defined responses to various circumstances—has computational time around 1 s for a one year simulation with perfect foresight. A key explanation of such difference is that linear programming, mixed integer and non-linear programming models are programmed in a high-level syntax interpreted and "solved" at run-time in a mathematical solver whereas EnergyPLAN is compiled and operated as an executable file at run-time. One way to reduce computational times in the solver-based approach is to use sample periods over the year trying to cover typical seasons and variation patterns. However, when calculating future renewable energy systems such short-cut becomes problematic since the chronological calculation of different types of energy storage becomes essential.

3. Politics and Planning

3.1. The Role of Politics in Optimisation Modelling

The use of optimisation models is tempting for decision-makers for two separate reasons. Firstly, politicians can make good use of expert studies based on well-established quantitative methods that end up with specific recommendations, as long as these are in line with their general policy. Criticising recommendations would constitute criticising economic rationality.

Secondly, politicians with a liberalist agenda and a strong belief in the market's ability to find optimal solutions are attracted to models that seek economically optimal investment strategies under existing market conditions. The best solutions occur, when investment decisions are left to market actors acting on market information. The invisible hand ensures that the sum of all private choices turns out to be the public's best option also (cf. [52]).

An example of a policy, where the two approaches were combined, is the Danish national energy strategy from 2005, *Energy Strategy 2025*. The then Danish Minister of Transport and Energy, Flemming Hansen (from the Conservative Party), underlined repeatedly that the government "wanted to use the market as basis" for the development of the energy sector. Renewable energy technology projects should only be initiated, if or when "the market demands more capacity", rather than through "politically forced expansion". Renewable energy should only be introduced to the extent that it provides additional economic benefits ([53], p. 9).

Basically, the Minister did not want to interfere with the market, unless serious market failures occurred. His main political goal was economic efficiency, based on the existing, and in his view well-functioning markets, even though he was content that a market-based solution appeared to have less environmental impact than many people feared, this was not an independent political goal for him.

Another example is the Danish Economic Council's evaluation of the Danish Government's policy on renewable energy sources during the 1990s [54–56]. In 2002, the council blamed the then Minister of Environment and Energy, Svend Auken (Social Democrats), for choosing an energy policy based on emotions rather than rational calculations based on models like Balmorel and the council's own DEMS; a model making projections for energy demands based on macro-economic projections ([56], p. 93).

Optimisation models may however reduce the role of the decision-makers to the role of administrators, as politics is reduced to an administrative affair. Likewise, members of society are reduced to consumers and their role as responsible citizens dismissed (cf. Sagoff [57]). The Danish Economic Council stated explicitly that the Danish energy policy of the 1990s should never have been implemented, and explained this failure by lack of economic analyses [54]. If optimal solutions can be found through the market itself, supported by computer-based virtual market imitations in cases of market failures ([56], p. 31), political deliberations become superfluous at best.

3.2. The Role of Politics in Simulation Modelling

Whereas optimisation modelling may turn the role of politics into administration, the use of simulation models and the model-external evaluation of scenarios leaves more room for an the political decision-making processes. This gives both politicians and engaged citizens the opportunity to deliberate on societal values and responsibilities without, by definition, being blamed for making inefficient sub-optimal decisions.

A core point in simulation modelling is that the realm of politics is recognized as a separate realm that should not be reduced to response to quantitative analyses. The purpose of making models of the energy system is not to replace politics but to service and qualify political deliberations. Political decision-making includes a number of hard choices between different developmental paths. Models can be used to support these decisions by calculating the most likely outcomes of various choices. In the end, decisions are basically political, though, because they involve a variety of considerations that cannot be reduced to matters of efficiency in relation to a general goal like economic wealth.

If we use climate change again as example, the politicians have to address a number of non-quantifiable considerations including: Which kinds of obligations do we owe to future generations? Does it change anything if the majority of these can be expected to live in foreign countries with different cultural values? Can we expect future generations to be richer and have more technological opportunities, and does this influence our obligations? Does our own level of wealth and capabilities influence our obligations? Should our country/region/municipality act more responsibly than our apparently less concerned neighbours, even though this may imply economic losses? Would this way of acting eventually bring new opportunities to posterity?

It is not possible to compute a way pass such difficult choices. Model builders can help by estimating consequences of diverse choices, based on the various assumptions, but, again according to Kuhn, they cannot relieve experts of the responsibility to make genuinely political decisions. Does this mean that simulation models must be kept value free in order to avoid interfering with political decision-making? The simple answer is that they cannot. In order to select parameters for the model, it is necessary to have an idea about which kinds of consequences are worth knowing. Some parameters are included, whereas others are left out. Does this make simulation model builders as prescriptive in their approach as optimisation modellers? In order to give a fuller answer to this question, a closer look at the role of the researcher is required.

4. The Role of Modellers and Planners

4.1. Optimisation Modelling

The optimisation model encourages the modeller to use computational measures on difficult issues and seek optimal investment strategies free of personal preferences in an effort to be objective. This is a too high ambition, though. To begin with, it is necessary to select the overarching goal, which makes optimisation assessments possible in the first place. For more than 200 years it has been discussed whether the final goal in economic optimisation analyses is total happiness or welfare, total preference satisfaction, or personal freedom of choice [58–64]. In general, economic wealth has been used as a proxy for the basic goals, particularly since the Kaldor/Hicks criterion of potential Pareto improvements replaced the Pareto optimum as an optimisation measure.

Sometimes optimisation calculations do include other considerations than total economic wealth, though. In the year 2000 British Green Book on public economic assessment, for instance, it is stressed that public assessments should attach more importance to consequences for disadvantaged groups of people than to others [65]. The argument is that the value of a marginal amount of money is inversely proportional to people's personal wealth. Most other Cost-Benefit-Analysis manuals ignore this issue.

Another example, where other kinds of considerations need to be taken into account, is the choice of discount rate. Different textbooks recommend different rates, and theorists have disagreed significantly about this since climate change became an issue for economists in the late 1980s, partly due to dissent on questions of distributive justice across generations (e.g., Nordhaus [66,67]; Cline [68]). Some recommend a rate as high as 6–8% or even more, whereas others recommend a rate close to 0%. The issue became heated again when the Stern Review on the economics of climate change argued for a low discount rate [69] and immediately was opposed by mainstream economists (Nordhaus [70]; Yohe and Tol [71]; Dasgupta [72]).

A number of similar choices about basic assumptions have to be made by the researcher. Much disputed examples are the value of statistical lives, monetization of environmental impacts, the construction of baseline-scenarios, choice of systems boundaries, and value transfers from other studies [64]. These assumptions often have a significant impact on the result, and textbooks therefore recommend sensitivity tests, where calculations are made with different values on the most uncertain or controversial issues.

These tests may easily undermine the results, though, if they are made thoroughly. In energy system modelling the most significant assumption is often the choice of discount rate. If calculations are made with discount rates as different as 8% and 0%, then the difference between the final results will be so large that the rest of the calculation becomes irrelevant and the optimisation assessments become useless. Consequently, in most cases, the chosen intervals between the values used in sensitivity tests are much smaller. This is typically legitimized with reference to some standard textbook recommendations, but these recommendations remain ethical and political despite their appearance as mere technicalities.

4.2. Simulation Modelling

If simulation models are used, the modellers' tasks will be different. First of all, the modeller is not expected to end up with a single solution. This does not mean that the modeller is not in a position to recommend: the basic point is only that such recommendations cannot be based on one model-based simulation alone, since the modeller typically puts forward more than one solution and will have to compare and use other kinds of arguments.

A second difference is that simulation modelling does not imply monetisation of all consequences. A modeller may choose to monetise in order to get an idea of probable economic outcomes of various options, but this is not obligatory. In most cases the various consequences of different choices are presented in disparate quantitative measures. The implicit assumption is that decisions can be made rationally without common denominators. Politics is basically about making hard choices in situations where various uneven, comparable but incommensurable, consequences and obligations need to be taken into consideration [50].

A third difference is that simulation models are suited for both forecasting and backcasting. *Forecasting* is used when political decision-makers need to have an overview of future implications of different current choices. Simulation modellers do not claim that there is only one optimal way to reach a future goal, nor do they aim to make predictions. Instead, they present a variety of possible paths and end states with dissimilar direct and indirect consequences.

Backcasting is used, when a future target, goal or end state is settled, and the various ways to reach the goal need to be identified. Backcasting is particularly important whenever there is a need for major changes. If current trends that are bound by past decisions, it may be necessary to set up a clear future goal or target in order to break from these trends and identify new pathways.

Comparing cost-effectiveness could be seen as a kind of backcasting, where the cheapest way to a future goal is sought, but these calculations are typically shortsighted and conservatively biased in a way that makes them unreliable in cases of major changes. Radically new steps typically appear economically inefficient in light of past decisions. If, for instance, a coal-fired plant was build 10 years ago and is expected to be functional 30 more years, it appears inefficient to install new wind turbines. In such cases, a wider horizon is needed to detach from past choices.

4.3. The Planners' Role and Use of Energy Models

The two approaches, optimisation and simulation, lead to different kinds of planning practice (Table 1). Both are opposed to the traditional *commander* model, which compares the politician to a captain on the bridge, who follows a subjectively determined course. Navigators and the engine room crew execute orders as efficiently as possible. The commander model also assumes that common people only are relevant as voters and taxpayers.

In one type of optimisation, which we shall call economistic (Economistic (from "economism") and scientistic (from "scientism") denote a viewpoint that economy respectively science is the principal frame of assessment.), common people are given a prominent role, but primarily as private consumers with a behaviour that can be modelled econometrically. Political decisions ought to satisfy as many private preferences as possible. The planners use optimisation models in order to identify the path that satisfies the largest number of preferences. It is assumed that market mechanisms will create the optimal situation, unless market failures disturb them. Rational politicians will only protect the market from force and fraud and compensate for market failures.

In the second type of optimisation, which is here called scientistic, the planners and technicians are the main actors. The "correct policy" is identified scientifically on the basis of strict calculations, and rational politicians follow their advice. Common people cannot be expected to act rationally and must be ruled and regulated through management systems. Efficiency does not have to be defined in economic terms in this model, but may be conceived in terms of energy consumption or CO_2 emissions. Still, in most cases, these kinds of models include economic considerations, in which case they tend to merge with the economistic optimisation model.

In the fourth model, the dialogue or deliberation model, all three groups of actors play active roles. First, the politician is neither a sovereign commander nor a compliant service assistant. Politicians are expected to listen to arguments from citizens and planners, but still have the responsibility to make final long-term decisions in areas, where even the best arguments leave various possibilities open.

Table 1. The various roles of politicians, planners and people in four different planning models described in the text. The coloured areas mark the most important actors in each model.

Title	Politicians	Planners	People
Commander model	Make decisions and give orders	Execute orders using planning tools	Voters and taxpayers
Optimisation model I (economistic)	Satisfy consumer preferences on the basis of efficiency calculations	Survey, aggregate and satisfy consumer preferences	Sovereign private consumers
Optimisation model II (scientistic)	Follow advices from the planners	Scientific computation of the correct (or necessary) policy	Objects of scientific management
Dialogue model	Issue guidelines, make final decisions	Advisors, initiators, and communicators	Actively involved citizens

Secondly, the planner acts neither as an instrument nor as a computer trying to satisfy private preferences. The planner assists the politician in making qualified decisions and in implementing them efficiently and with due considerations to affected parties. This includes critical assessment of political arguments. Simulation models are helpful, because they assess the possible outcomes of political decisions and invite to dialogue with citizens and affected parties. This means, thirdly, that the citizens cannot be reduced to subjects of scientific management or to preference optimising consumers. The dialogue model follows the tenets in Dewey's pragmatism about education, participation as conditions for democracy [73] as citizens are expected to act responsibly, to be able to separate their private preferences from public needs and requirements, and to be influenced by arguments. This demand for communication, dialogue, and deliberation makes simulation modelling more appropriate than optimisation modelling. Simulations can be made on the basis of a variety of assumptions, and the emphasis on awareness means that the calculated outcomes of various decisions should enter the public dialogue in order to stimulate and qualify it.

The calculated outcomes become argumentative resources in societal situations of techno-scientific concerns and controversy as when climate change demands radical change away from fossil energy systems. The contribution to the making of publics (Marres [4]) is a fundamental difference to the meaning of the outcome of optimisation models, that may function as debate blockers.

5. Concepts of Rationality in Decision-Making

It is sometimes argued that optimisation models are preferable to simulation models, because they are objective all the way through and lead to decisions that are rational, whereas the use of simulation models opens a door for subjectivity and irrationality, either from politicians or from politicising modellers. Optimisation models do include an element of subjectivity, too, of course: the consumers' subjective preferences, but these are surveyed and measured objectively and subsequently calculated rationally in the optimisation model.

This argument rests on controversial conceptions of objectivity and rationality. Both are connected much too closely with the use of replicable methods that make results independent of people with allegedly subjective and ever-changing emotions, opinions, attitudes, and values. Science must avoid subjectivity, the argument goes, and the only way to do this is to rely on clear-cut methods and measurements.

The fact that all researchers, who follow certain rules and methods, will end up with similar result does not in itself make them rational, though. Relevance and usefulness have to be legitimized, and this legitimization cannot itself be based on methodical surveys and calculations. The construction and revision of methods must be based on rational arguments. But as these rational arguments cannot be based on methodical surveys and calculations, it does not make sense to try to reduce rationality to the use of quantitative methods.

Similarly, if the ideal of objectivity implies that the results must be absolutely certain and expected to stand forever, the conception is ripe for revision. This does not mean that everything goes, nor that results are open for interpretation without reservation. Arguments can be the soundest available and investigations made the most rational way at a certain moment in time, and yet their relevance and credibility may fade over time. The ideal of scientific research founded on rock-hard ground and the quest for unlimited certainty must be replaced by a less demanding ideal (cf. the classic discussion in Bernstein [50]).

Perfect answers are extremely hard to find once questions become complex. As the American philosopher John Rawls has put it, our faculty of judgment becomes overburdened, once the complexity of an issue reaches a certain level, and there is no longer just one answer that can be called reasonable [74]. Instead of unquestionable truths we should strive for qualified answers supported by well-considered arguments.

Answers should be as consistent as possible, of course, and coherent with other chunks of knowledge that we consider valid. Still, incoherencies may also be stimulating challenges that call for new insights and reinterpretations. To be rational is not to aim for absolute and eternal certainty, but to look for and learn from what is considered the best arguments available so far—as well as from mistakes and inconsistencies.

The optimisation models' use of computations based on a single parameter like costs may appear attractive, because the results appear precise and unequivocal compared with deliberative weightings of a plurality of relevant considerations. However, the downside of optimisation modelling offsets these advantages. The reduction of citizens to consumers, the reduction of politics to administration, as well as the large number of underlying assumptions about key parameters such as the discount rate, distributive issues, and the value of statistical lives and environmental goods, all make the results much more uncertain than they appear at first sight.

Simulation modelling are of course also based on underlying assumptions, however as the approach does not identify a single development path as optimal, the process is more open and the conception of an ideal solution is not present. Rather, in simulation models the controversial and basically political themes are brought out into the open. The possibility on dialogue decreases the separation between research-based knowledge formation and communities and policy formation (Marres [4]). The modeller can still assist by explaining why certain paths are preferable to others on basis of the best arguments they are aware of. They cannot and should not try to remove the complications and controversies though, since it would be a highly irrational thing to do. In situations of techno-scientific controversy it is seen as a principal quality to have public involvement in such matters. The concept of 'hybrid forum' was developed by Callon et al. [3] to characterize the type of democratic process performed during public controversies over techno-scientific issues. Hybrid forums organize deliberative processes in which heterogeneous actors from affected groups like NGO's, experts, politicians and officials—collectively deal with problems in which they are all implicated (Callon et al. [3]).

6. Cases to Illustrate the Points

Table 2 summarises the main points made above. Again it should be emphasized that the two approaches are described as archetypes. In real life modelling, hybrids are also found. Still, the use of archetypes highlights the implicit or explicit theoretical understanding behind the different models.

A few examples, where both a simulation and an optimisation approach have been applied to answer the same question, can illustrate how the two approaches may lead to similar or dissimilar answers. These cases also illustrate how the simulation approach results in information for several alternatives while the optimization approach typically presents only one optimal solution. Moreover, it shows that real-life application of models rarely follows exactly one of the archetypes exactly.

The first case is the role and inclusion of photovoltaics (PV) in the design of a suitable and cost-effective implementation of the Danish policy to implement a fossil-free energy supply by 2050. Two different analyses were prior to—and provided inputs for—a decision made by the Danish Parliament.

In 2006, the Danish Society of Engineers (IDA) made a proposal for a Danish future energy strategy [75]. The study was followed up in 2009 [76] and 2015 [77]. These studies analysed different alternatives by use of EnergyPLAN. In 2006, PV was significantly more expensive than wind power, but the PV industry estimated that costs would decrease along with investment and a gradual implementation. The study therefore included a strategy to implement PV before it became economically competitive and to increase PV in Denmark to 5000 MW in 2050. As a Plan B, it proposed to replace PV with wind power, if costs were not decreasing as expected.

In 2009 the Danish Government established a Climate Commission to give advice on implementing the fossil free energy supply policy. Models and analyses were based on the Balmorel optimisation model [78]. The model was constructed to identify the least-cost solution given a certain number of political restrictions. The result was that PV was not part of the proposed main scenario for many years due to the high investment costs at the time. The analysis did calculate different scenarios that included PV, but the Climate Commission merely looked at the wind-based scenario that was computed to be most cost-effective. These results were a serious problem for the Danish PV industry and made it difficult to get PV back on the agenda.

Table 2. Overview of characteristics in archetypical optimisation versus simulation models.

Summary	Optimisation Models	Simulation Models
Definition	A model that internally establishes an optimal energy system design; typically through optimising decision variables for an objective function subject to constraints.	A model that simulates the behaviour of a user-defined energy system design through the same mathematical principles as the optimisation models or through other principles.
Purpose	To identify the optimal solution.	To calculate the performance of possible future systems and to find a set of solutions for an open evaluation process.
Result	Strive for results in one optimal solution	Results in several alternative solutions
Modeller/Computer relation	Crucial design decisions are made inside the computer on the basis of in-built rules, restrictions and presumptions	Design decisions are made outside the computer, after a spectrum of options are considered by the modeller
Typical technical characteristics	Detailed in modelling of the current system	Detailed in the modelling of future systems
	Long computation time and/or low temporal resolution	Short computation time and high temporal resolution
Planning theory and methodology	Well-suited for forecasting.	Well-suited for backcasting.
	Intends to be well-suited to prescribe the future.	Intends to be well-suited to discuss the future.
Politicians role	Receive and accept authoritative results from experts. Limited room for political decision-making.	Politics is recognized as a separate realm and includes a number of choices between different development paths
Planners role and decision-making model	Well-suited for the Economistic and Scientistic models	Well-suited for the Dialogue model.
Risk analysis methodology	Sensitivity analysis	Alternatives assessment
Concepts of rationality	Strive for smooth operationality, and hide or disregard controversial political themes.	Strive to bring the controversial and political themes into the open.

This case illustrates how the optimisation approach has problems with including new technologies, which are not yet market ready. It also illustrates how the exclusion of such technologies is carried out "by the computer" on the basis of costs only, and that one has to make various scenarios with different restrictions of favourable price projections in order to include emerging technologies.

Another case is the role of district heating in future Danish energy strategies analysed by the same two different models. The first model in 2008 and 2010 used a simulation approach, whereas the second one in 2014 used an optimisation approach. Both reached the conclusion that district heating should play a larger role in the future, but they reached the conclusion in quite different ways.

The 2008 [79,80] and 2010 [48] studies used the simulation model EnergyPLAN. The analyses focused on buildings located inside or next to existing district heating areas. The study analysed 10 different alternative ways of supplying these houses with heat using three different energy systems. The consequences were calculated for all alternatives in terms of influence on resulting primary energy supply, CO_2 emissions, and costs. The analysis is described in details in [79] and Figure 3 shows one set of the many results.

Strengths and weaknesses of the different technologies were also discussed in [79] which provided alternatives and concluded with a recommendation of one of the presented paths. The discussion included assessments of different technologies, system parameters, and consequences, as well as a variety of relevant short and long-term considerations.

In 2014 a similar investigation was conducted for the Danish Energy Agency [81] by consultants using the optimisation model Balmorel. This study essentially set out to answer the same questions, and reached a conclusion that was quite similar to the study from 2008. Only one solution was presented, however: the optimal one. It did not compute, present nor discuss the same variety of alternatives as the study from 2008.

Citizens and politicians were thus presented with a final result, founded on a predetermined set of premises, presuppositions, estimates and methodological assumptions. Energy policy appeared as a merely neutral technical issue, and ethical and political questions seemed possible to deal with rationally by the use of prefabricated algorithms constructed by expert model builders.

Maybe the most important difference between the two approaches is that in the *simulation* approach also poor and sub-optimal solutions are analysed, put forward and can be discussed while such solutions are lost in the *optimisation* approach. Consequently, there is a significant difference in the ability to raise awareness on why the poor solutions are poor and how poor (or maybe not so poor after all) they are.

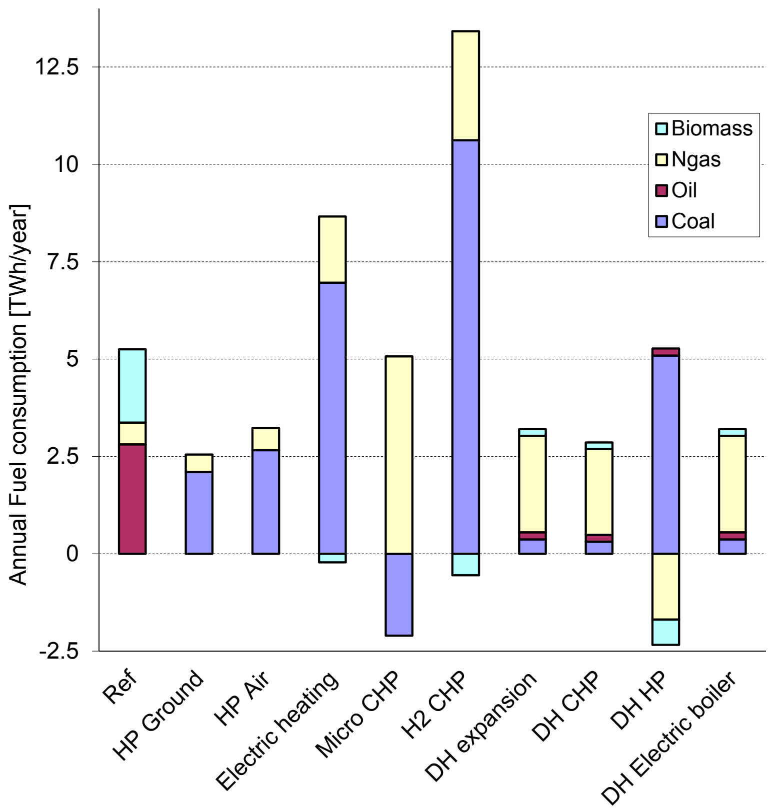

Figure 3. Example of output from a study using a simulation model and approach for the assessment of a number of different alternatives. The diagram shows different scenarios' influence on primary energy in Danish energy supply. Some alternatives reduce some fossil fuel components while others increase compared with the reference of the current technology. DH is district heating; HP are heat pumps; CHP are Combined Heat and Power. Reproduced from [48,79].

7. Conclusions

This paper has focused on energy system analysis models meant for the analysis of future sustainable energy solutions at the national level. Typically such models have a focus on the integration of various renewable energy resources as well as the transformation of existing energy systems. While we recognize the importance of the epistemic process of new knowledge formation in situations of societal crisis, it is of critical importance to investigate the way the different approaches emphasize public debate and learning. We claim that the type of democratic process generated during public controversies over techno-scientific issues is important, because new hybrid forums may organize deliberative processes in which heterogeneous actors from affected groups collectively deal with problems in which they are all implicated.

The archetypal *optimisation* approach assumes that optimal solutions can be identified based on mathematically solving on objective function with respect to optimal energy unit sized. This is a computational process before the political decision-making takes place. Politicians receive authoritative results from experts. Typical optimisation models are slow and detailed in the description of current systems, but in theory well-suited for forecasting with the purpose of *prescribing the optimal future* on the basis of the incorporated presumptions.

The archetypal *simulations* approach assumes a variety of options that should be analysed and compared on different parameters. Relevant options should be presented in a political decision-making process where alternatives are assessed. Politicians receive different options and substantiated recommendations. Typically simulation models are fast and detailed in their ability to compare different future options and well-suited for back-casting with the purpose of *debating the desired future*.

Optimisation models may also calculate different options, but in practice the models are not very well suited for this as they need to be nudged to include other technologies. If the purpose is to assess different options simulation models are more appropriate with its user defined system configurations. Simulation models may be used to identify optimal solutions, but this is not their main purpose or strength.

Both kinds of models have strengths and weaknesses, but simulation models have an advantage that make them suited for long-term decision-making in democratic societies. They present the citizens and politicians with a variety of possibilities that are shown to depend on political choices about controversial issues. These choices may not all be optimal paths from a strictly economic perspective based on current knowledge, but they present a variety with potential choices with quantitative and qualitative distinctions.

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