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Analyzing the effects of uncertainties on the modelling of low-carbon energy system pathways

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Abstract

Decarbonization is an important goal of the future energy transition, but its modelling is also subject to several uncertainties. Here we investigate the impacts of such uncertainties through analyzing the overall performance and operation of a modelled national energy system undergoing deep decarbonization. Finland was chosen as a case, as it intends to become carbon-neutral already by 2035. Uncertainties in costs, energy consumption, and renewable resource potential and how they affect the operation of a modelled energy system is analyzed using a Monte Carlo method linked to a national energy system model with hourly resolution. The importance of the different uncertainties for the overall system indicators such as annual cost, CO₂ emissions, and reliability are assessed. The impacts on different modelled low-carbon pathways are compared. For the Finnish case study, the projected energy consumption seems to be the most important uncertainty factor for the future energy system scenarios (e.g. for the CO₂ emissions), followed by the production of wind power and the potential of biomass. The results indicate that addressing input uncertainties will be highly relevant for energy system modelling when pursuing decarbonization. None of the modelled cost-optimal decarbonization pathways stands out as fully resilient in this respect.

Highlights

- The impacts of uncertainties on low-carbon energy system modelling are analyzed.
- Monte Carlo analysis is used to examine uncertainties' effects on modelled systems.
- Finland is used as a case with the year 2050 data.
- Energy consumption seems to be the most significant uncertainty factor.

Keywords

Energy system modelling; Uncertainty; Monte Carlo uncertainty analysis; Scenarios; Finland

1 Introduction

Energy system models often form the basis for elaborating carbon-neutral energy system pathways that are urgently needed to achieve the targets of the Paris Climate Agreement [1]. However, energy system modelling, particularly system optimizations, often employ deterministic values for input parameters. This poses a risk for suboptimal decisions or performance, as any uncertainty in the model's input parameters may render the model's output uncertain and unreliable [2,3]. If uncertainties in the modelling process are not addressed, it will be challenging to evaluate how well the modelled energy system pathways would meet their given environmental or economic targets if the input parameters transpired to be different from the expected. If uncertainty is neglected and only point values from quantitative scenario analyses are presented, it can also lead to the false assumption that there is more confidence in those estimates than is the case [4]. Uncertainty is also closely related to energy system resilience, as resilient systems are better equipped to accommodate future variations. IPCC encourages to quantify uncertainty as much as possible [5], while also paying close attention to the language used to communicate uncertainty [6]. However, the adequacy and reliability of IPCC's highly standardized procedures are still under debate [7].

Including uncertainty in energy system modelling has received increasing interest in literature, and there are several different approaches, as the possible sources of uncertainty are numerous [8,9]. One option is to incorporate uncertainty directly to the energy system modelling. In the context of energy system optimization under uncertainty, commonly used methods include stochastic optimization [10–12], robust optimization [13–15], fuzzy programming [16,17], and, less commonly, quadratic programming [18]. Stochastic methodology can be used to describe the short-term uncertainty of the temporal fluctuations in e.g. demand [12,19,20], market prices [10,12,21], power plant availability [22] and wind power production [20,23,24], among others. Multiple studies also state that stochastic solutions differ from the deterministic solutions due to e.g. overvaluation of intermittent energy sources [10–12,25]. Regardless of the selected methodology, incorporating uncertainty is also closely connected to portfolio selection and investment planning [16,20,21,26,27] as well as environmental performance evaluation [28]. On a broader scale, the concept of uncertainty analysis can also be extended to comparing the impact of various policy [10,29] or technology [30] scenarios. Some studies focus on evaluating the structural uncertainty of an energy system model by MGA (modelling to generate alternatives) [26,31].

Alternatively, uncertainty analysis can also be conducted with a deterministic model with Monte Carlo methods [32,33], or by exploring large changes in the input data, such as the weather data [34,35] or sudden shocks to the power system [36]. However, one of the most commonly used methods for uncertainty analysis is local sensitivity analysis, in which the impact of the assumed key input parameters is investigated one parameter at a time. However, this method cannot properly capture the impact of the whole parameter space and the outcome of the study may be limited. Here, we apply a form of global sensitivity analysis, in which all parameters are varied simultaneously using Monte Carlo methodology, similarly to [32] with a case study for an optimal distributed energy system design of a Swiss urban neighborhood. IPCC also regards Monte Carlo simulation as a suitable method for uncertainty analysis [37].

Finland was chosen as the case study for this paper because of its ambitious climate targets [38,39] and data availability. The current goals of the Finnish energy policies include banning the use of coal by 2030 and reaching full carbon-neutrality by 2035. Finland has also made decisions in the past to include nuclear power in its future energy production, contrary to most of the EU countries [40,41]. The current main low-carbon energy resources in the Finnish primary energy mix are nuclear power, forest biomass, hydropower, and wind power. The share of renewable energy in final energy consumption is 41% (2017) [42]. Like in many other northern countries, combined heat and power (CHP) is important in Finland due to the cold climate, and it represents around one quarter of the electricity production. The future pathways and the challenges of the

Finnish energy system have been discussed in literature, e.g. [23,29,43–50]. This study is a continuation of our previous work on Finnish low-carbon energy system pathways [51]. Even though many of these studies address some aspect of future uncertainty, such as lower biomass availability [29,45], demand uncertainty [29,46], and weather conditions [47], these analyses are mainly done with separate scenarios addressing a single uncertain parameter. To our best knowledge, the future Finnish energy system pathways have not previously been subject to an uncertainty analysis with a wide systematic coverage of the uncertain parameters. Also, the energy system as a whole will be addressed in the modelling, including power, heat, industry, and transport sectors.

The main research question of this study is to which extent uncertainties would affect the performance of a modelled energy system, which would be a highly relevant question for policy decision-making and evaluation of energy system scenarios. The aim is to quantify to which extent will uncertainties in cost, consumption, and renewable resource potential affect the operation of a modelled energy system and the overall system indicators, such as annual cost, CO₂ emissions, and reliability. In particular, the performance of various kinds of cost-optimized future low-carbon energy system scenarios will be compared to better understand the resilience of different types of energy systems against modelling uncertainties. Along these lines, the energy system scenarios which show the highest resilience against changes in the modelling input will be identified. Also, the question of how the existing energy system assets would stretch to accommodate future uncertainties will be explored. Furthermore, the uncertain input parameters which are the most relevant for energy system modelling will be identified, with the intention of providing a viable methodology to select the most decisive factors for future research.

This paper is organized as follows: Section 2 describes the methodologies of the study: the energy system simulation model, optimization and sensitivity analysis. Section 3 presents the case study and input data. The results are discussed in Section 4, and the conclusions are presented in Section 5.

2 Methodology

2.1. Energy system simulation model

The methodology of the study is based on a national-scale energy system simulation model, implemented in MATLAB (see schematics in Fig. 1 and Appendix A Fig. A.1). The model incorporates all aspects of an energy system, including electricity, heat, and fuel; also, all end-use energy sectors are included. An earlier version of the energy system simulation model is presented in [29] (utilized e.g. in [51]), though the model is slightly updated for the purposes of this paper. The energy system is simulated on hourly basis over a year to consider the dynamics and interactions of its different segments. The model employs a 1-hour time step for electricity and heat, while fuel demands e.g. in transport are considered on an annual scale due to the large inertia (i.e. storage) of fuels. The model also includes various flexibility measures, such as power-to-heat (P2H), power-to-gas (P2G), biomass-to-liquid (BTL), electric vehicles (with vehicle-to-grid (V2G)), and thermal and electrical storages. Though the analyses in this study are on the national scale, the method proposed could also be used on other scales, e.g. for cities.

In the model, the hourly heat and power production is simulated based on merit order and rules, given in the following. For each hour of the year, the heat and power production are determined according to the following procedure:

Fig. 1. Schematic of the analysis approach illustrating the coupling of optimization and sensitivity analysis to the simulation model which forms the core of the methodology. Optimization is used to determine the optimal energy system capacities, whereas in the sensitivity analysis, non-historical input data is varied and the model output variations are analyzed.

1. Production from non-dispatchable plants (here wind, solar, nuclear, industrial CHP, run-of-river hydro and residential fuel boilers);
2. Heat production: enough plants are dispatched (CHP, heat-only boilers, P2H) to meet the heat demand. The order of the plants is based on the lowest marginal cost, always starting with stored heat;
3. Electricity surplus handling: surplus electricity is offered to different uses (sector-coupling), starting from P2H (including charging of thermal storages), charging electric vehicles and electrical storage, power-to-gas, export, and finally, curtailment;
4. Electricity production: in case of no surplus, enough plants are dispatched (hydropower, import, electricity-only plants) to meet the electricity demand. The order of the plants is based on the lowest marginal costs;
5. Final balancing: if electricity demand is not met, 1) P2H is removed, 2) idle CHP is added, and 3) heat-only plants are used for balancing. Possible excess heat is stored.

In the model, plants are aggregated by plant type and fuel, and the ramping capabilities of plants are taken into account. The operation of non-dispatchable plants is based on historical data. CHP plants are assumed to operate solely based on heat demand, which was found out to match the historical data quite well (see Section 3.2). Cross-border import is regarded as a “virtual power plant”, the marginal cost of which is based on the exogenous electricity market price. In addition, the marginal cost of the last 1000 MW of import capacity is doubled to simulate market congestion. Detailed modelling of the electricity market was outside the scope of this paper, which may cause uncertainties especially in the international market’s availability to absorb export. The modelling of hydropower differs from other plants to reflect the balancing capabilities of reservoir hydropower and the effect of varying inflow: the available hydropower capacity is divided into 10 subplants, and the marginal cost of each subplant depends linearly on the water level in the reservoir. The maximum marginal cost of hydropower, i.e. the cost when the reservoir level is at its minimum, is determined in the model by calibration. Residential electric heating was considered as electricity demand and left out of the detailed simulation.

After determining the heat and power production, the fuel demands of transport and industry are filled with the available fuels using the lowest-cost principle, including biofuel production.

2.2. System optimization

The present energy system simulation model can also be applied to energy system optimization, and examples of combining energy system simulation with external optimization can be found in [52–54]. This kind of *simulation-based optimization*, where the target value of the optimization is calculated with a separate simulation model, also helps to bridge the gap between the two archetypes of energy system models, i.e. simulation and optimization [55].

Fig. 1 demonstrates the coupling of the optimization and the simulation model. In order to construct cost-optimized low-carbon energy system scenarios and determine the optimal capacities, the optimization aims to minimize the total annual system cost, which is one of the outputs of the simulation model. The annual system costs include annualized investment costs, O&M costs, fuel costs, net costs of power import and CO₂ emission costs. The optimization variables are the plant and storage capacities of the energy system, and the optimization constraints include: 1) -95% reduction in CO₂ emissions (compared to 1990), 2) covering hourly heat and electricity demands, and 3) limiting the annual wind curtailment to 5%. The optimization uses deterministic single values for input parameters; here the median value of the input parameter ranges was used. The optimization process is used to construct future energy system scenarios, whereas the reference system (here Finland in 2016, see Section 3) is not optimized.

2.3. Sensitivity analysis

To uncover the impact of input variation on the performance of a modelled, cost-optimized energy system, Monte Carlo –based uncertainty analysis was applied, in which the energy system simulation model is repeatedly evaluated for different samples of the uncertain input parameters. Here, the aim is to obtain a distribution of the model outputs as a response to the uncertain parameter variations, as opposed to a single deterministic output value. Furthermore, to overcome the limitations of local sensitivity analysis, global sensitivity analysis is utilized and all uncertain input parameters are varied simultaneously.

The parameter samples (N samples of M uncertain input parameters) are generated from given uncertainty ranges with the random number generator of MATLAB® [56]. To ensure adequately dispersed random samples and good coverage of the whole parameter space, the number of Monte Carlo evaluations is chosen high, $N = 10\,000$. This number is considered adequate for the analysis, as the model output shows good convergence at $N > 8000$ (see Fig. A.2). For simplicity and a wide coverage of the uncertainty ranges, uniform input parameter distributions are assumed. The calculations are performed in a parallel fashion on a computing cluster.

After the Monte Carlo evaluations, the most significant input parameters are determined with a simple correlation analysis: the significance of each input parameter is evaluated by calculating the correlation coefficients between the input parameter variation and model outputs.

It is worth noting that there is also a wide variety of other, often more complex methods for sensitivity analysis, such as the two-step methods in [32] and [8]. However, the aim here is to implement a mathematically simple method, which would 1) be able to assess the importance of parameters directly from the Monte Carlo analysis, 2) would not be computationally heavy, and 3) would not require additional

screening steps. These goals are motivated by the relatively high number of uncertain input parameters included here ($M = 36$, see Section 3.1) to cover a variety of uncertain factors, including consumption, costs and renewable potentials, and a non-linear complex simulation model. Similar metrics for sensitivity analysis have been used by e.g. [33].

3 Case study analysis of Finland

The case chosen here for detailed analysis is Finland, which represents an interesting case due to its ambitious climate policy, but also high per-capita energy use [1]. Also, this case and the selected scenarios directly continue our previous work on low-carbon scenarios [51]. Here, the effect of uncertain parameters both on the modelling of the existing energy system assets (the 2016 system) and on cost-optimized low-carbon energy system pathways in 2050 will be studied. Plant capacities of the 2016 Finnish energy system are readily available [57,58], listed in Table 1. The capacities in the future low-carbon scenarios are determined with cost optimization (see Section 2.2). Similarly to [51], we mainly focus on different levels of nuclear power, wind power, bioenergy and cross-border transmission capacity as these may form the major pillars in the future Finnish energy system and thus, could affect the overall energy system resilience.

Table 1. Plant capacities in the reference system (Finland in 2016), aggregated by plant type. The model further divides the capacities by fuel. Capacities are mostly based on [57,58].

Plant type	Capacity (MW _e or MW _{th})
Power capacity	
CHP-DH	4002
Industrial CHP	2555
Nuclear power	2764
Hydro power	3025
(of which run-of-river) ^a	(900)
Wind power	1598
Solar PV	35
Power-only	2140
Import/export ^b	5100/-3620
Heat capacity	
Heat-only	13320
Heat pumps	167
Electric boilers	115
Solar heat (GWh) ^c	19
Storage	
Thermal storage in DH (GWh) ^d	17
Hydro reservoir (GWh) ^b	4385 (maximum), 2332 (minimum)

^a Assumption based on [74].

^b Based on [62].

^c GWh/year, based on [42].

^d Based on [75].

Eight different future scenarios with varying levels of nuclear power and transboundary power transmission capacity will be considered, listed in Table 2. Based on earlier work on energy system optimization [51], the level of nuclear power will also affect the use of variable renewable energy (VRE), in particular wind power. Various levels of future nuclear power were analyzed here, because Finland's carbon-neutral energy policies will continue to rely on nuclear power [38,39]. Nuclear power levels between 0 and 6700 MW (approx. 63% of the 2016 annual electricity demand) are based on a combination of existing, planned, and hypothetical nuclear units [51]. The scenarios on the transboundary power transmission capacity were included to analyze the energy system resilience in case of a lower international power trade, as the current Finnish energy system relies much on the Nordic electricity market. The numerical values of the transmission scenarios are based on the projected transmission capacities in 2016, 2030, and 2050. One special scenario with a lower biomass use is also considered, limiting non-industrial forest biomass use to residential firewood only, reflecting on the ongoing debate on the sustainability of forest biomass for climate change mitigation [59,60]. In addition to the nuclear capacity, the total capacity of industrial CHP and residential fuel boilers are also left outside the optimization as these are considered as “must” options due to their highly strategic nature in Finland.

Time series input data on production and demand are based on historical data [57], whereas annual consumption of the reference year is based on [42,61]. Plant efficiencies and ramping limits are also based on historical data. Hydro inflow is calculated based on hydropower production and hydro reservoir level data in 2016 [62]. For market price of electricity, historical Nord Pool data for 2016 is used for the temporal price distribution [62]. Heat demand is calculated based on ambient temperature values from Central Finland [63]. For investment costs, an interest rate of 5% is used.

Table 2. Scenarios analyzed in this study. The transmission capacity scenarios are based on the existing 2016 capacities (5100 / -3620 MW), assumed 2030 capacities (5800 / -5460 MW) and assumed 2050 capacities (6760 / -6760 MW). The assumed future values are based on the future plans of the Finnish TSO Fingrid [76] and own assumptions.

Scenario	Nuclear power (MW)	Import/export (MW)	Biomass limitations
NUC 6700 EXC 6760	6700	6760 / -6760	-
NUC 4300 EXC 6760	4300	6760 / -6760	-
NUC 2800 EXC 6760	2800	6760 / -6760	-
NUC 1600 EXC 6760	1600	6760 / -6760	-
NUC 0 EXC 6760	0	6760 / -6760	-
NUC 2800 EXC 5800	2800	5800 / -5460	-
NUC 2800 EXC 5100	2800	5100 / -3620	-
NUC 2800 EXC 6760 BIO low	2800	6760 / -6760	Non-industrial forest biomass limited to residential firewood.
Reference 2016	2760	5100 / -3620	-

3.1. Uncertainties in input parameters

The uncertainties in the input parameters are here imposed to: 1) level of consumption, 2) renewable resource potential, and 3) cost data in 2050. The parameters are listed in Appendix B, and the total number of non-zero uncertain input parameters is 36. The uncertainty of consumption refers here to the uncertainty of future annual consumption projections, not to intra-annual temporal uncertainty. Two extreme scenarios of future

consumption are considered based on earlier work [29]: “High 2050” and “Low 2050”. The uncertainty range of consumption is then a continuous range between these two extremes. Considering the uncertainty of consumption could be highly relevant when considering future energy scenarios, as the overall level of consumption will undoubtedly have an effect on the performance of an energy system.

Equally important is to consider the limits on renewable energy use, as our scenarios aim for near carbon neutrality. The uncertainty of sustainable biomass use and wind power production are considered here. The assumed limits of renewable energy use and their uncertainty ranges in 2050 are listed in Tables B.3 and B.4. The uncertainty of wind power production was represented by uncertain capacity factor. The change in capacity factor was introduced by a parabolic addition to the hourly load duration curve, keeping the hourly minimum and maximum wind power production unaltered. The uncertainty of solar production was excluded from the study, as the role of solar power in future Finnish energy scenarios is quite limited.

Finally, the uncertainty ranges of costs are listed in Tables B.1, B.2 and B.4. Uncertain cost ranges are assumed for fuel costs, investment costs, electricity market price and CO₂ emission cost. To construct cost-optimal low-carbon scenarios, the optimization uses the medium value of the uncertainty ranges, labelled “2050 medium” in the input data. As for the consumption, the average between “High 2050” and “Low 2050” consumption scenarios is used in the optimization.

As the investment costs of nuclear power are subject to a considerable uncertainty [64] and even a negative learning rate [65], which may not be considered in the cost database sources used [66,67], a special case is included reflecting more recent outcomes at Olkiluoto (FI), Flamanville (FR) and Hinkley Point C (UK) nuclear sites under construction [68–70]. The investment costs in this additional case are assumed to be 5500–7500 €/kW in 2050, with the median value of 6500 €/kW, and 5500 €/kW in 2016.

3.2. Model calibration

The model is calibrated with historical hourly and annual data (Finland 2016), considering mainly the maximum production capacities of power and heat plants. The plant capacities are scaled down to match the maximum historical production since the reported nominal plant capacities [58] do not match the hourly production data [57] used for model validation. The maximum marginal cost of hydropower is also calibrated to match the total historical hydropower production as well as possible (see Section 2.1 for details of the hydropower modelling). The results of the calibration are presented in Table 3 and Fig. 2, and further calibration results are presented in Supplementary Information. The calibration aims to match the annual historical data, whereas the hourly historical data is used only for visual comparison.

After calibration, the model shows a decent match with the historical data. The main reasons for discrepancies between the simulation outcome and historical data arise from higher use of coal, due to the strictly cost-based simulation and a relatively low coal price. For the same reason, gas-CHP is non-existent in the simulations, replaced by other (mainly heat-only) plants. Much of the differences in the hourly comparison between simulated and historical productions are due to intricacies of the electricity market, such as long-term bidding strategies or the effect of international trade, which are outside the scope of the present modelling approach and would require very detailed modelling of the international power market. These discrepancies in the market modelling are present especially in the hourly hydropower and power-only production. However, sequential merit-order-based simulation, like the method used here, is an often-used method for national energy system modelling, resembling the procedures of e.g. [71] and the widely recognized EnergyPLAN model [72]. In addition, especially the simulated CHP production shows a good correlation (0.82) with the historical data.

Table 3. Comparison between the calibrated model's output indicators and the historical data.

Indicator	Historical	Simulation	Error
Total annual CO ₂ (MtCO ₂)	43.20	48.71	13%
RE share of primary energy	34%	33%	-1 %-points
RE share of final energy	39%	36%	-3 %-points
RE share of electricity production	45%	41%	-4 %-points

Fig. 2. Comparison between simulated and historical (Finland 2016) primary energy use as part of the model calibration.

4 Results

In this section, the results of the global sensitivity analysis are presented both for the modelled reference and low-carbon energy system scenarios, described in Sections 2 and 3. First, the cost-optimized energy system scenarios are presented, followed by the uncertainty analyses, and the discussion on the most influential input parameters. The aim is to study the modelled, cost-optimized energy systems' response to the given input parameter variation, reflecting the future uncertainties befalling the energy systems.

4.1. Optimized low-carbon energy system scenarios

The compositions of the low-carbon energy system scenarios for Finland in 2050 (see Table 2) are optimized with the procedure described in Section 2.2 using deterministic input values. The deterministic overall indicators of the optimized scenarios are presented in Table 4, and further details are presented in Supplementary Information. All scenarios had a CO₂ emission reduction target of -95% (2.7 MtCO₂), in addition to cost minimization. The optimized scenarios are in line with our previous work [51]. Wind power capacity increases with decreasing nuclear capacity, indicating a trade-off between these two main forms of

Table 4. CO₂ emissions, annual system costs and the share of renewables of the scenarios with deterministic input values. The annual costs also display the costs with the higher nuclear investment costs in brackets.

Scenario	CO ₂ emissions (MtCO ₂ (change from the year 1990))	Annual costs (100 = 2016 level)	Share of renewables ^a
NUC 6700 EXC 6760	1.0 (-98%)	118 (135)	60%
NUC 4300 EXC 6760	2.1 (-96%)	116 (127)	69%
NUC 2800 EXC 6760	1.0 (-98%)	117 (124)	79%
NUC 1600 EXC 6760	1.4 (-97%)	118 (122)	87%
NUC 0 EXC 6760	1.7 (-97%)	119 (119)	98%
NUC 2800 EXC 5800	2.1 (-96%)	120 (127)	78%
NUC 2800 EXC 5100	2.0 (-96%)	123 (130)	77%
NUC 2800 EXC 6760 BIO low	10.8 (-80%)	130 (137)	67%
Reference 2016 ^b	48.7 (-10%)	100 (103)	33%

^a Share in primary energy consumption.

^b 2016 consumption and input data.

electricity production in the future Finnish energy system. In addition, heat production shows a clear trend of electrification: heat production shifts from the currently dominant CHP to heat pumps (on average 70% of production). CO₂ emissions appear to be quite insensitive to nuclear capacity, whereas the annual costs seem to be the lowest at middle-range nuclear capacities. However, this would also depend on the future cost of nuclear power. If a higher nuclear investment cost of 6500 €/kW were used reflecting recent developments (see Section 3.1), the annual costs would clearly increase especially in the scenarios with higher nuclear capacities (up to 14% compared with zero nuclear). As for the impact of power exchange capacity, the wind power capacity slightly decreases with decreasing exchange capacity (up to -16%, as export capacity decreases by 46%), highlighting the importance of cross-border transmission capacity for effective wind power integration. Costs and CO₂ emissions increase with decreasing exchange capacity (up to 6% and 103%, respectively). Limiting biomass availability mainly increases fossil fuel consumption to substitute for the missing biomass, increasing both CO₂ emissions (18 %-points) and annual costs (11%).

4.2. Response of the reference case (Finland 2016) to uncertainties

First, the effect of uncertainties on the modelling of an energy system is considered through the reference case. The response of the modelled reference energy system (Finland 2016) to the future 2050 uncertainties is presented in Figs 3 and 4, using the procedure described in Section 2.3. Of the overall indicators, CO₂ emissions shows the most variation (standard deviation 21%), followed by the annual cost (13%) and share of renewables (5%). However, the security of supply seems to be inadequate, as seen in the level of power and heat not supplied. Especially crucial is the error in the power supply, at most 6000 ppm or 0.6% of the total consumption, which is thousand times higher than the current level of 4.4 ppm [73]. As median values, the power shortage was at maximum 2300 MW and occurring for 1.1% of hours in a year. These results indicate that the existing energy system would not always be able to meet the overall electricity demand, and the current energy system may thus not be resilient enough to accommodate future energy consumption.

The fuel composition (Fig. 4a) shows most variation in the amounts of fossil and biomass use, which also causes the CO₂ emission variation. A more detailed analysis also shows variation between the different fuels,

such as oil, coal and wood. Similarly, the most variations in power and heat production are present in CHP and other fuel-based production methods, and power import. These results indicate that the fuel-based plants are sensitive to fuel cost variations: the operation order of plants, and here also power import, depends on the relative cost order of fuels. The relative fuel costs thus also affect the primary fuel composition. However, interestingly hydropower, the operation of which is also affected by the merit-order-effect, seems to be completely unaffected by the input variation, and is instead run at full capacity for most of the time. Thus, fuel-based production, such as CHP, seems to be more susceptible to input parameter variations than non-fuel-based production.

Fig. 3. The reference energy system's (Finland 2016) response to modelling uncertainties. The legend of these so-called “violin plots” is presented in the lower right corner. In the reference case, due to the lack of an optimized scenario, the red dot represents the value with deterministic median input parameter values.

Fig. 4. The reference energy system's (Finland 2016) response to modelling uncertainties in terms of **a)** fuel composition, **b)** electricity production and **c)** heat production. See legend in Fig. 3.

4.3. Response of the low-carbon energy system scenarios to uncertainties

Selected results about the response of the modelled optimized low-carbon energy system scenarios to the modelling input uncertainties are presented in Figs. 5, 6, and 7. Regarding the CO₂ emissions (Fig. 5a), all scenarios exhibit higher median emissions than in the original optimization with deterministic input values, although the emission distribution is unevenly accumulated on the lower end. The increased emissions are most likely caused by increased fossil use, which also causes a similar effect on the share of renewables (Fig. 6): almost all scenarios exhibit lower renewable shares than originally. The scenario “NUC 2800 EXC 6760 BIO low” seems to be a minor exception: as the use of biomass was here more limited than in the other scenarios, there were less options in the primary energy composition, and the change in the median CO₂ emissions and share of renewables is less pronounced. However, due to the higher fossil use, the respective distributions are wider and resemble the distributions in the reference case.

As for the annual cost (Fig. 5b), all scenarios have higher costs than in the optimization with deterministic input values. This highlights the importance of including input variation in the modelling-based decision-making: deterministic input values seem to result in too low and therefore unreliable cost estimates as the modelled scenarios are exposed to input parameter variation. In addition, cost comparison between the scenarios seems to be virtually impossible, as the cost ranges significantly overlap with each other. A similar incomparability can be seen with the CO₂ emissions, with the exception of “NUC 2800 EXC 6760 BIO low” which clearly has the highest emissions. However, the share of renewables does not exhibit such overlapping, being mostly dependent on the level of nuclear power.

Finally, the scenarios perform quite similarly in terms of the power and heat supply adequacy (Fig. 7), and almost all scenarios have both power and heat supply error. Unlike in the reference case, the heat supply errors (~1000 ppm of consumption) are much higher than the power supply errors (~50 ppm). The reason for this disparity is most probably the difference in power and heat supply options: as the optimized energy systems are sized exactly according to the deterministic consumption without any spare capacity, meeting any additional demand may be particularly difficult in the heat sector, where cross-border import is not an option. This trade-off is most prominent in the scenario “NUC 6700 EXC 6760” with excessive nuclear capacity: it is the only scenario without any power supply error, but has the highest error in the heat supply. This scenario also has the lowest total heat production capacity of all scenarios: due to the abundance of near-constant nuclear power, there is less need for non-electric heat production capacity, reducing the modelled system’s ability to handle higher heat consumption. As all scenarios had errors in power and/or heat supply adequacy, no scenario seems to stand out as the most resilient to future input parameter variations regarding the security of supply.

An example of the underlying fuel composition and power and heat production is presented in Fig. 8, with scenario “NUC 2800 EXC 6760”. The greatest variations in fuel consumption (Fig. 8a) arise from biomass use, wind power and power export. It can be argued that the variation between forest and non-forest biomass reflect the respective fuel cost variations like in the reference case, whereas the variation in the power export arises from the varying wind power production. In the electricity sector (Fig. 8b), there is little variation besides wind power and export, whereas in the heating sector (Fig. 8c), power-to-heat experiences most variation, possibly stemming from the varying wind power production.

To further analyze the effect of highly uncertain nuclear investment costs, the results of the special case with a higher cost range of 5500-7500 €/kW (see Section 3.1) are presented in Fig. 9. Here only the annual costs are presented, as all other discussed indicators (CO₂ emissions, the share of renewables, and power and heat supply errors) were virtually identical, justifying the robustness and reproducibility of the Monte Carlo analysis. This also highlights that the nuclear investment cost only affects the total annual costs, not the

modelled energy system operation or performance. As with the deterministic case, the cases with more nuclear capacity have a higher cost range: the difference between the median costs of the highest and lowest nuclear capacity is 9.8%. However, as with the original case, all cost ranges are overlapping with each other.

Fig. 5. Low-carbon energy system pathways' response to modelling uncertainties in terms of a) CO₂ emissions and b) annual system costs. See legend in Fig. 3.

Fig. 6. Low-carbon energy system pathways' response to modelling uncertainties in terms of the renewable share (in primary energy). See legend in Fig. 3.

Fig. 7. Low-carbon energy system pathways’ response to modelling uncertainties in terms of **a)** power and **b)** heat supply errors, measured as the share of missing supply in total annual consumption. See legend in Fig. 3.

Fig. 8. Example low-carbon energy system pathway’s response to modelling uncertainties in terms of **a)** fuel composition, **b)** electricity production and **c)** heat production. Here the case “NUC 2800 EXC 6760” is selected as the example case. See legend in Fig. 3.

Fig. 9. Low-carbon energy system pathways’ response to modelling uncertainties in terms of annual system costs in the case of higher nuclear investment costs. See legend in Fig. 3.

4.4. Significance of input parameters

Finally, the significance of the different input parameters is evaluated by correlation analysis. Tables 5-9 present the correlation coefficients between selected indicators (CO₂ emissions, annual costs, share of renewables and errors in power and heat supply) and the five most influential parameters. The most influential parameters were here determined as the parameters with the highest average absolute correlation coefficients.

Overall, the level of consumption seems to be the single most significant factor for all selected indicators, highlighting that the choice of consumption projection is extremely relevant when constructing and modelling future low-carbon energy system scenarios. Other influential parameters are wind power capacity factor, CO₂ price and the potentials of wood and agro-biomass. Besides the parameters mentioned in the tables, the influence of most of the other parameters is very weak, correlation coefficients being near zero. This indicates that the variation in the output values is affected mainly by a handful of input parameters, and the uncertainty of most of the 36 uncertain input parameters (see Section 3.1 for detailed description) could have been safely neglected without affecting the output variance.

Based on these modelling results, it would seem that the level of consumption is more influential for CO₂ emissions and costs than the CO₂ price, implying that reducing consumption could be effective in reducing CO₂ emissions and costs. Secondly, the capacity factor of wind power seems to affect all the main indicators of the energy system, as wind power is an integral part of the low-carbon scenarios and any change in its overall production has widespread effects throughout the modelled system. Apart from the consumption and wind power, the annual costs are affected by the CO₂ price in the more fossil-using scenarios (reference and the “BIO low” case), whereas the annual costs of the wind-heavy low-carbon scenarios are affected by the investment cost of wind power plants. Furthermore, the influence of the wood and agro-biomass potentials on the CO₂ emissions is particularly important for the case of Finland, as the Finnish energy policies rely heavily

on biomass use. Errors in the biomass availability evaluations is thus implied to have negative impacts on reaching the future emission targets.

Regarding the power and heat supply errors, the level of consumption and wind power capacity factor are, perhaps unsurprisingly, the only significantly affecting parameters, as they directly determine the levels of demand and the production variance of the most dominant electricity source in the low-carbon scenarios.

To ensure that consumption did not overshadow any other correlation, all the Monte Carlo runs were repeated without the consumption variation. Removing the consumption variation did not change the results substantially, but the correlation coefficients of the other parameters increased, strengthening their influence. In addition, the cases with the higher nuclear costs (see Section 3.1) had identical correlation coefficients, which illustrates that the correlation analysis seems to be insensitive to the numerical values of input parameter variation.

Table 5. Correlation coefficients between the CO₂ emissions and the most influential input parameters.

Scenario	Consumption	CO ₂ price	Wood potential ^a	Agro-bio potential ^b	Wind capacity factor
NUC 6700 EXC 6760	0.68	-0.25	-0.20	-0.25	-0.11
NUC 4300 EXC 6760	0.80	-0.25	-0.21	-0.21	-0.08
NUC 2800 EXC 6760	0.73	-0.25	-0.20	-0.23	-0.15
NUC 1600 EXC 6760	0.76	-0.24	-0.20	-0.22	-0.17
NUC 0 EXC 6760	0.77	-0.24	-0.19	-0.21	-0.19
NUC 2800 EXC 5800	0.81	-0.24	-0.19	-0.18	-0.13
NUC 2800 EXC 5100	0.80	-0.23	-0.19	-0.21	-0.17
NUC 2800 EXC 6760 BIO low	0.86	-0.23	-0.27	-0.01	-0.17
Reference 2016	0.93	-0.27	-0.01	0.00	-0.02

^a Potential (i.e. maximum use) of non-industrial wood.

^b Potential of agro-biomass.

Table 6. Correlation coefficients between the annual costs and the most influential input parameters.

Scenario	Consumption	Wind capacity factor	Wind investment cost	Wood price ^a	CO ₂ price
NUC 6700 EXC 6760	0.75	-0.38	0.31	0.25	0.08
NUC 4300 EXC 6760	0.76	-0.41	0.31	0.23	0.12
NUC 2800 EXC 6760	0.72	-0.45	0.36	0.23	0.09
NUC 1600 EXC 6760	0.71	-0.47	0.38	0.22	0.10
NUC 0 EXC 6760	0.69	-0.49	0.39	0.21	0.10
NUC 2800 EXC 5800	0.77	-0.40	0.32	0.23	0.12
NUC 2800 EXC 5100	0.78	-0.36	0.32	0.24	0.12
NUC 2800 EXC 6760 BIO low	0.72	-0.40	0.31	0.06	0.37
Reference 2016	0.74	0.00	0.01	0.10	0.61

^a Price of non-industrial wood.

Table 7. Correlation coefficients between the share of renewables and the most influential input parameters.

Scenario	Consumption	Wind capacity factor	CO ₂ price	Agro-bio potential ^a	Wood potential ^b
NUC 6700 EXC 6760	0.25	0.65	0.20	0.22	0.27
NUC 4300 EXC 6760	-0.36	0.55	0.26	0.29	0.29
NUC 2800 EXC 6760	-0.38	0.53	0.23	0.25	0.30
NUC 1600 EXC 6760	-0.58	0.42	0.22	0.23	0.27
NUC 0 EXC 6760	-0.75	0.26	0.21	0.20	0.23
NUC 2800 EXC 5800	-0.54	0.47	0.25	0.25	0.25
NUC 2800 EXC 5100	-0.52	0.47	0.23	0.25	0.29
NUC 2800 EXC 6760 BIO low	-0.52	0.63	0.22	0.36	0.01
Reference 2016	-0.79	0.06	0.32	0.02	0.00

^a Potential of agro-biomass.^b Potential of non-industrial wood.**Table 8.** Correlation coefficients between the error in the power supply and the most influential input parameters.

Scenario	Consumption	Wind capacity factor	Waste price	Heat pump inv. cost	El. boiler inv. cost
NUC 6700 EXC 6760	0.04	-0.04	0.01	-0.01	0.00
NUC 4300 EXC 6760	0.24	-0.20	0.02	-0.02	-0.02
NUC 2800 EXC 6760	0.40	-0.29	0.03	-0.02	-0.02
NUC 1600 EXC 6760	0.41	-0.22	0.02	-0.02	-0.02
NUC 0 EXC 6760	0.42	-0.25	0.02	-0.02	-0.01
NUC 2800 EXC 5800	0.37	-0.26	0.02	-0.02	-0.02
NUC 2800 EXC 5100	0.44	-0.30	0.02	-0.02	-0.02
NUC 2800 EXC 6760 BIO low	0.29	-0.24	0.01	0.00	0.00
Reference 2016	0.90	-0.04	0.00	-0.01	0.00

Table 9. Correlation coefficients between the error in the heat supply and the most influential input parameters.

Scenario	Consumption	Wind capacity factor	Oil price	CO ₂ price	Waste price
NUC 6700 EXC 6760	0.75	-0.17	-0.01	0.01	0.01
NUC 4300 EXC 6760	0.55	-0.30	-0.02	0.01	0.02
NUC 2800 EXC 6760	0.62	-0.36	-0.01	0.00	0.02
NUC 1600 EXC 6760	0.60	-0.37	-0.02	0.00	0.02
NUC 0 EXC 6760	0.59	-0.37	-0.02	0.00	0.02
NUC 2800 EXC 5800	0.62	-0.35	-0.01	0.00	0.02
NUC 2800 EXC 5100	0.64	-0.35	-0.01	0.00	0.02
NUC 2800 EXC 6760 BIO low	0.62	-0.35	0.01	0.00	0.00
Reference 2016	0.26	0.04	-0.14	0.21	0.02

5 Conclusions

In this study, the impacts of uncertainties on the modelling of various low-carbon energy systems have been investigated in terms of overall performance and operation. Our research question was to which extent will uncertainties in cost, consumption, and renewable resource potential affect the operation of a modelled energy system and the overall system indicators, such as annual cost, CO₂ emissions, and reliability. The case study was Finland in the year 2050. The impact of modelling uncertainties on various cost-optimized low-carbon energy system scenarios was assessed as a continuation of our previous work [51], as well as on the modelled existing 2016 Finnish energy system. It was also assessed which uncertain input parameters were the most significant.

In the presented methodology, a deterministic national hourly energy system simulation model was used, including all sectors of the energy system: electricity, heat, and fuel. The uncertainty analysis was performed with Monte Carlo methodology: the simulation model was repeatedly evaluated for different samples of the uncertainty. The projected uncertainty ranges for the level of consumption, cost data and renewable resources were based on literature. The model output variations were further examined to determine the most influential parameters via calculating the correlation coefficients between the output and input variations.

The uncertainty analysis reveals significant variations in the model's output indicators. In particular, in all of the studied low-carbon scenarios, the CO₂ emissions and annual costs were higher than in the deterministic case. This highlights the importance of including uncertainties in the input when providing analyses for modelling-based decision-making: in the case study, deterministic input values seem to result in too low and therefore unreliable cost estimates as the modelled low-carbon scenarios are exposed to input parameter variation. In addition, including uncertainty makes cost comparison between the scenarios quite difficult. Of the various low-carbon energy system pathways, no modelled scenario seems to stand out as the most resilient to input parameter variation regarding the annual costs, CO₂ emissions, or security of supply. In addition, the results suggest that fuel-based production, such as CHP, seems to be more susceptible to input parameter variation than non-fuel-based production.

As for modelling the existing system (Finland in 2016), the results show that the existing system would not in any case reach a deep decarbonization target of -95% of the CO₂ emissions by 2050, nor always meet the 2050 electricity demand: the median value for power not being supplied was 0.1% of the total consumption. It is thus implied that the existing assets of the Finnish energy system are not able to fully cope with the 2050 level of consumption, prompting the need for possible capacity expansion and changes in the power mix.

In the case study, the most significant input parameter in regard to the annual CO₂ emissions, system costs, share of renewables, and power and heat supply adequacy was found out to be in this case study the level of consumption, followed by wind power capacity factor, biomass potentials and CO₂ price. These results are in line with previous research, e.g. [24,32,33]. The results indicate that the choice of consumption projection in future low-carbon energy system modelling is extremely relevant. Furthermore, the influence of the wood and agro-biomass potentials on the CO₂ emissions would be particularly important for biomass-reliant energy systems such as the case of Finland.

The results highlight that uncertainty and variation in the input of energy system models has a significant impact on the energy system performance. In addition, the presented methodological approach appears to be able to reveal the range of the impacts and provide insight into the most significant input uncertainties. For example, the variation in the output values is indicated to be affected mainly by a handful of parameters. In particular, the level of projected consumption seems to be highly relevant. Secondly, the yield of wind power affects all the main indicators of the energy system, as wind power is often an integral part of low-carbon scenarios and any change in its overall production has widespread effects throughout the modelled system,

e.g. through sector-coupling. Furthermore, using single deterministic values for costs and consumption may result in unreliable cost and performance estimates, so including uncertainty in energy system modelling seems highly relevant to modelling-supported decision-making to avoid suboptimal decisions. Careful discretion may be needed when using deterministically optimized energy system scenarios in decision-making, particularly with deterministic consumption projections: though the scenarios themselves may be optimized, they may not respond to input parameter variation as well as one might expect, and comparison between options may transpire to be difficult.

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Author contributions

S.P.: Conceptualization, Methodology, Formal analysis, Visualization, Writing - Original Draft,
P.D.L: Supervision, Conceptualization, Writing - Review & Editing.

Appendix

A. Additional methodology

Fig. A.1. Schematic of the simulation model.

Fig. A.2. Justification of the 10 000 Monte-Carlo runs with one example case and example output (annual cost). The shaded area represents 95% confidence intervals of the average (black line).

B. Input data

Table B.1. Assumed fuel costs, based on [1,10,42,77]. Fuels not listed are assumed to have zero cost.

Fuel	Cost (€/GJ)			
	2016	2050 low	2050 medium	2050 high
Oil	7.0	6.7	9.8	11.7
Coal	2.9	2.8	4.2	4.8
Natural gas	6.8	6.3	9.7	11.0
Peat	3.7	3.6	5.4	6.2
Nuclear ^a	1.1	1.1	1.1	1.1
Other wood ^b	5.8	5.5	7.7	9.5
Agro-biomass	5.6	5.3	7.4	9.1
Biogas	10.4	9.2	11.4	13.6
Biofuel	12.1	12.1	13.4	14.7

^a Based on [78] and author's assumptions.

^b Forest biomass that is not a direct residue from the forest industry.

Table B.2. Assumed technology costs, based on [66,67]. Values other than investment are presented in the format “2016 value / 2050 value”, if there is a difference between the years.

Technology	Investment costs (€/kW)				Fixed O&M (% of invest.)	Variable O&M (€/kWh)	Lifetime (years)
	2016	2050 low	2050 medium	2050 high			
Hydropower ^a	2 750	1 170	2 790	3 800	1.3%	4.0	60
Wind power	1 020	630	790	950	2.5/2.7%	2.8/2.1	25/30
Nuclear power ^b	4 500	3 350	3 750	5 000	2.1/1.6%	2.5	60
Solar PV	1 080	330	410	460	0.9/1.3%	0.0	30/40
CHP ^c	1 300	900	1 100	1 600	2.3/2.4%	4.5/4.0	25
Power-only	1 300	900	1 100	1 600	2.3/2.4%	4.5/4.0	25
Heat-only	60	40	50	250	3.3/3.4%	1.1/1.0	25
Residential fuel boiler	580	200	590	1 000	7.4/7.5%	0	20
Heat pumps	700	500	530	1 000	0.3/0.4%	3.3/3.9	25
Electric boiler	70	20	60	170	1.6/1.5%	0.8/1.0	20
Solar heat (€/MWh)	430	290	330	360	0%	0.2/0.4	30
Power-to-gas ^d	1 000	140	280	420	4%	-	30
Gas-to-liquid (€/TJ) ^e	6 300	4 050	4 550	5 050	4%	-	30
Biofuel conversion (€/TJ) ^f	17 500	10 490	13 990	16 790	3%	-	20/25
Electricity storage (k€/MWh)	708	50	135	305	0.2/1.2%	2.1/1.6	15/30
Heat storage (€/MWh)	580	390	470	540	0.5/0.6%	0	20/25

^a The same cost range used also for run-of-river hydropower.

^b In addition to these database values, we also include a special case reflecting the more recent outcomes at Olkiluoto (FI), Flamanville (FR) and Hinkley Point C (UK) nuclear sites under construction [68–70]. The investment costs in this additional case are assumed to be 5500–7500 €/kW in 2050, with the median value of 6500 €/kW, and 5500 €/kW in 2016.

^c The same cost range used for both district heating and industrial CHP.

^d Partly based on [79].

^e Partly based on [80].

^f Partly based on [81].

Table B.3. Assumed renewable energy potentials based on [44,50], and their present use [61]. In addition to these uncertain bioenergy potentials, potentials for wind power (50 GW [1]), solar PV (53 PJ [82]), solar heat (5.4 PJ [50]) and hydropower (+500 MW to present level [50]) are considered.

Renewable energy source	Present use (2016) (PJ/a)	Potential in 2050 (PJ/a)		
		2050 low	2050 medium	2050 high
Industrial wood residue ^a	226	189	214	240
Other wood	119	178	208	238
Agro-biomass	4	38	58	78
Waste	24	16	25	34
Biogas	4	3	7	10
Biofuel	8	30	35	40

^a Potential assumed directly proportional to the industrial production volume, defined in the consumption.

Table B.4. Additional uncertain parameters.

Parameter	Unit	Present level (2016)	2050 low	2050 medium	2050 high	Source of data
CO ₂ emission cost	€/tCO ₂	8	50	115	180	[1]
Average electricity market price	€/MWh	32	47	57	66	[44]
Wind power capacity factor ^a	-	0.25	0.24	0.29	0.36	[63]

^a Uncertainty range obtained from historical weather data of 2010–2018: a theoretical wind power capacity factor was calculated by averaging the hourly wind speed data from three locations across Finland, representing the geological spread of wind power plants, and calculating the production with Vestas V90-3MW turbine's (80 m) power curve.

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