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Comparing the Energy System of a Facility with Uncertainty about Future Internal Carbon Prices and Energy Carrier Costs Using Deterministic Optimisation and Two-Stage Stochastic Programming

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Abstract: For an organisation, one aspect on the path to a decarbonised future is the cost-optimal decarbonisation of their facilities' energy systems. One method to guide the decarbonisation is internal carbon pricing. However, the design process of decarbonisation pathways, guided by internal carbon prices, can be challenging, since the energy system environment consists of many uncertainties. Despite the numerous uncertainties and existing methods to address uncertainties during the optimisation process, the optimisation of a facility's energy system is often done by assuming perfect knowledge of all relevant input parameters (deterministic optimisation). Since real-world decisions can never be based on perfect knowledge and certain decisions might lead to path dependencies, it is important to consider the robustness of a solution in the context of developments that vary from the assumed scenarios. So far, no academic work has analysed the potential benefits of using an optimisation method that considers uncertainty about future CO_2 prices and energy carrier cost as two important input parameters during the optimisation process. This publication closes the knowledge gap by optimising a real-world energy system of a manufacturing site with two-stage stochastic programming and comparing it with methods of deterministic optimisation. The results show considerably more robust results for the solutions generated by stochastic programming. The total cost deviation does not exceed 52%, while the deviation of the deterministic results reaches up to 96%. The results also indicate that organisations should not analyse their energy systems by only considering uncertain internal carbon prices, but should examine the effects together with other important but uncertain parameters.

Keywords: internal carbon pricing; two-stage stochastic programming; deterministic optimisation; energy system optimisation; decarbonisation; proxy prices; optimisation results' robustness

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1. Introduction

With the Paris Climate Agreement, the international community widely acknowledged the need to fight the global climate crisis [1–4]. Efforts to fight the climate crisis are currently focused on reducing carbon dioxide and other greenhouse gas (GHG) emissions. This motivates organisations to, among other things, decarbonise their energy systems. Due to the complexity of designing decarbonised energy systems, energy system optimisation models (ESOMs) are a common tool to support decision-makers [5,6]. In the context of optimising an organisation's decarbonised energy system, bottom up ESOMs are used during the decision process. These models usually try to represent a local energy system and allow the analysis of different technology options over long time horizons [7] (often more than 20 years). With this analysis, cost-efficient transformation pathways or the optimal energy system configuration can be explored, considering a variety of framework conditions [6] (refer to [8] for a detailed overview on energy system modelling). Often, these ESOMs are designed to work under deterministic framework conditions that assume that all relevant input parameter values are exactly known [9] (referred to as deterministic ESOMs or deterministic optimisation). However, the majority of input parameters that influence the results of ESOMs, hold a great degree of inherent uncertainty [5] (e.g., renewables generation or future energy demands). The uncertainty is further increased by the high number of relevant input parameters, their significant interwovenness, and the analysis of long time horizons [5,10–12]. One uncertain parameter, which has gained attention in the last years, is the price for carbon dioxide (also called CO_2 price, carbon price, or carbon pricing in the scope of this paper).

CO_2 prices are used to guide GHG emission reductions by increasing the costs of actions with high emissions [13,14]. Usually, it is defined as a certain price for a metric ton of CO_2 or CO_2 equivalents [13]. The concept of carbon pricing can be implemented by regulatory bodies or voluntarily by an organisation [13,14]. The latter is called internal carbon pricing [13], where an organisation can define the type and value of the carbon price independently. The number of organisations that have implemented some form of internal carbon pricing has been growing over the last years [15–17]. To define the value of an internal carbon price is a significant challenge, which the academic literature describes as the "right price trap" [13,18,19]. The reasons for this challenge are manifold. One might be that an organisation that choses to use some form of internal carbon price is at risk of using a price which is higher or lower than (future) actual carbon prices [20–23], which might lead to competitive disadvantages. Another reason might be that the parameters CO_2 price, energy demand, and costs in the power sector can develop dynamics that vary from predictions [24]. Both add further complexity and uncertainty to the design process of an organisation's energy system and the decarbonisation pathway.

Without properly addressing the uncertainties in the context of energy systems, model insights might be limited and lead to suboptimal decisions once the real-world parameters deviate from their assumed model input values [5,6]. The literature agrees that the inherent uncertainties of ESOMs' input parameters are a "key issue for energy models" [6] and a major challenge that is "at best underplayed and at worst ignored" [6] [5,6,25,26]. Consequently, incorporating methods to account for uncertainties is identified as a best practice in the context of ESOMs [6,25]. One common way of addressing uncertainty in the context of deterministic ESOMs is by defining scenarios, altering certain input parameter values, and calculating optimal solutions for each scenario [5,6] (referred to as scenario analysis). However, the model must have perfect knowledge about the future values of all relevant parameters within each scenario and might generate very different results for each scenario. The variety of scenario results might not help decision makers, as they do not know which solution should be chosen. Additionally, decision makers must plan an energy system with the uncertainty being revealed "only at a later time in an 'act now then learn' fashion" [6]. Deterministic models do not allow this sequentiality of the decision process to be properly represented. Another method for the evaluation of uncertainty in the context of deterministic models is sensitivity analysis, which gives an indication of the robustness of the model results once input values change [27]. This type of analysis is more a "postoptimality analysis" [9], which models should not rely on to examine the role of uncertainty [9].

Methods which are explicitly designed to address uncertainty and which have been applied to ESOMs are "Monte Carlo analysis, stochastic programming, robust optimisation and modelling to generate alternatives" [6]. For the Monte Carlo analysis, a probability distribution for the uncertain variables is required and a high number of samples of the random variables are generated that are fed into the model. The set of outputs can be evaluated with statistical techniques [6]. Robust optimisation uses a deterministic set representation of the uncertain variables [6]. The method tries to generate a solution that is feasible for any variation of uncertainty within a set [6,28]. Modelling to generate alternatives is, broadly speaking, a method that tries to find alternative solutions in the "near optimal solution space" [6]. Stochastic programming (SP) is the only method to represent sequential decision-making that characterises real-world decision-making in the context of energy systems [6]. The result of a SP optimisation is a "single optimal hedging strategy" [6] that provides one robust solution for all defined scenarios, taking the assumed uncertainties into account [6]. With this strategy, the model's solution is in the best position to adapt to all defined future scenarios once the uncertainty resolves [29]. Additionally, this single strategy allows the problem of multiple scenario results, which might leave the decision makers in a "quandary", to be avoided [6]. When comparing SP with deterministic solutions, the literature shows that the SP strategy does not match the average or interpolation of any deterministic solution [6]. This implies that SP generates insights that go beyond the findings of the deterministic results [6].

Therefore, SP is a well-suited method to "explore optimal near-term planning strategies that hedge against future uncertainty" [25]. Due to the long lifetimes of energy system investments, robust investment strategies are important, since the risk of being locked-in to costly technology configurations increases [30,31] (referred to as path dependencies). Path dependencies arise when a certain investment pattern (e.g., specific technology) is optimal for one scenario but contradictory to scenarios where input parameters are different [27,32]. Even though adequately incorporating uncertainties into ESOMs can complicate the optimisation model, it can improve the robustness (decrease the fragility) of ESOMs' optimal solution and reduce the chance of misleading decision makers [6,33].

Due to the importance of incorporating uncertainty in the optimisation process, one recommendation is to implement SP into "new or existing model[s]" [6] that would allow more than scenario or sensitivity analysis [6]. Additionally, analysing the influence of different uncertain parameters in the context of energy system optimisation increases the value of optimisation by "broadening the uncertainty space" [34].

1.1. Literature Review

The academic literature already contains several publications that analyse SP and ESOMs. Hu et al. simulate the impact of uncertain electricity demand increase, gas prices, and GHG regulations on the U.S. electric power sector's investments [35]. Mavromatidis et al. analyse an office building in Zurich, Switzerland and its energy system design with two-stage SP under energy demand and solar radiation uncertainties [5]. Yu et al. develop a two-stage SP model to optimise the design and operation planning of a hybrid renewable energy system with uncertainty regarding the energy generation and demand [36]. Schwarz et al. optimise a residential district with a two-stage stochastic mixed-integer linear model to optimise the thermal storage units [37]. Lima et al. develop a two-stage SP model to optimise the expansion planning of a distribution system considering uncertainties regarding the renewable generation, the demand, and the energy prices [38]. Yang et al. use two-stage SP to analyse the impact of uncertainties regarding energy prices, renewable energy intensity, and load demands on an energy system of a hospital [39]. Kostelac et al. examine the response of a "multi-energy industrial prosumer" with uncertainty regarding the day-ahead electricity market [40]. What is missing from the academic literature is the use of two-stage SP in the context of an organisation that optimises its energy system with uncertain internal CO_2 prices, as well as energy carrier costs.

1.2. Aim of This Work

So far, no publication has analysed the influence of these two uncertain parameters on energy system design and operation planning by comparing the robustness of two-stage SP and deterministic optimisation methods.

This work closes the identified knowledge gap by comparing the optimal energy system design of a manufacturing site and its robustness in the context of uncertain CO_2 prices, as well as energy carrier costs. The optimal energy system design is generated with deterministic optimisation and two-stage SP, which allows a broad comparison of different optimisation methods. A real-world facility serves as an exemplary energy system and the optimisation horizon stretches till 2040.

The remainder of this paper is structured as follows. Section 2 briefly describes the optimisation model and the theory behind (two-stage) SP. Additionally, all relevant model input values are defined. In Section 3, the model results are presented. Section 4 discusses the results and limitations of this work. The discussion is followed by a conclusion that also pinpoints promising areas for future research.

2. Materials and Methods

2.1. Optimisation Model and Methods

For this work, the SP method is implemented in DISTRICT. DISTRICT is a mixed-integer linear programming (MILP) tool, developed at Fraunhofer ISE in the General Algebraic Modeling System (GAMS) [41–44]. DISTRICT allows the optimisation of energy systems at the scale of city districts down to single industry processes. The model optimises the installed technologies and the operation of these technologies for a predefined time horizon. Its objective is to minimise the total discounted system cost, outlined in Equation (1).

$$C_{total\ cost} = \sum_{z=1}^{Z} \left[C_{total\ variable\ costs,z} + C_{total\ fix\ costs,z} + C_{electricity\ import\ costs,z} + C_{CO_2\ costs,z} + C_{annuity,z} \right] \quad (1)$$

where: $z \in \mathbb{N}^Z$ defined time horizon.

SP (sometimes referred to as stochastic optimisation) was introduced by Dantzig and expanded by Wets and Birge [6,9,45–47]. SP analyses situations in which an initial decision must be made with uncertainty about the future scenario states and decisions. The general model setup is a recourse model, where some variable values must be fixed before information on the relevant uncertainties are known (“here and now” variables). Other variables must be fixed once the uncertainty resolves (“wait and see” variables) [6,9,48,49]. In contrast to deterministic methods, the SP method does not provide an optimal solution for one scenario but an optimal hedging strategy across all defined scenarios. This hedging strategy provides a solution for each individual scenario, which is more expensive than the deterministic solution, but the cost does not increase as much once the scenario setting deviates from the assumed scenario setting (compared to the deterministic solution).

The number of decision stages defines the SP model type. A setting where one initial situation (“here and now”) is followed by one future decision where the uncertainty is resolved (“wait and see”) is called two-stage SP [9,29,48]. Since the uncertainty is resolved in the second stage, the second-stage becomes a deterministic optimisation problem [29,48]. Figure 1 illustrates the two-stage SP setup.

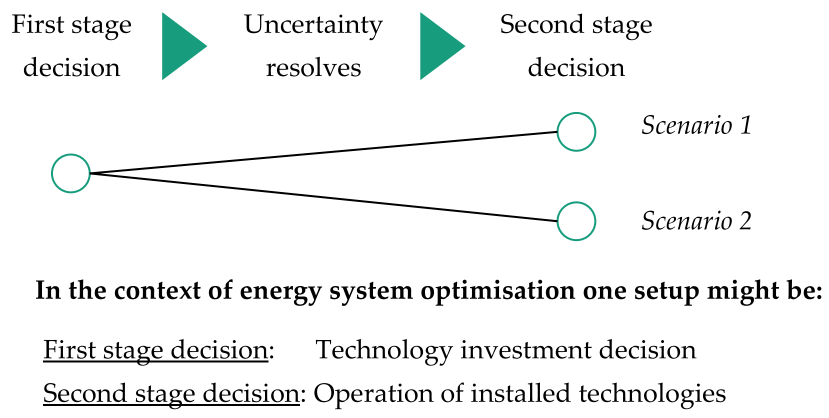


Figure 1. Decision tree for a two-stage SP model, based on [50].

In theory, the decision situation can be extended to more than two decision stages, which makes the decision problem increasingly difficult [9]. Figure 2 shows an exemplary three-stage decision problem.

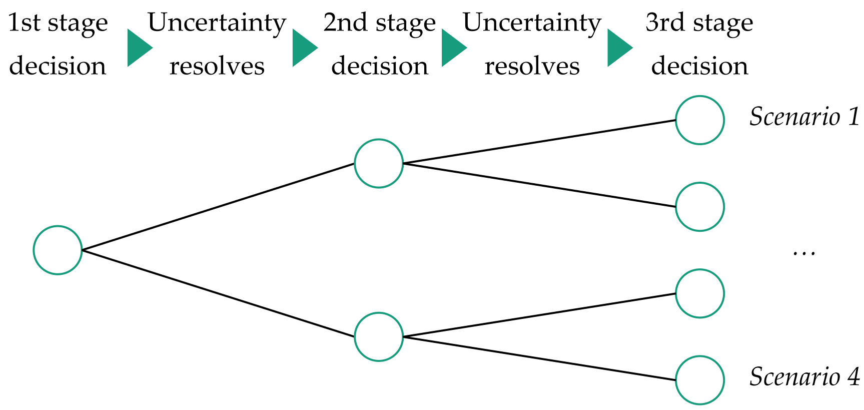


Figure 2. Decision tree for a multi-stage SP model (three stages) based on [51].

As Figure 2 suggests, SP is affected by the "curse of dimensionality" [25,27]. "The number of decision variables grows exponentially with the number of uncertain parameters and the number of uncertain time stages" [25], which can result in "computationally intractable problems" [27]. Due to this increase in dimensionality and the fact that SP is solved by finding the solution of the equivalent deterministic model, only a limited number of variables can be defined as uncertain [6]. The exact limit on the number of uncertain variables is dependent on the structure and complexity of the model, as well as on the available computing power. In the academic literature, the number of stages is usually between two and three, while the number of possible scenarios (or "states of the world", SOWs) is limited to 8–10 [6,25,27]. Usher et al. underline that, even though the two-stage stochastic program is the simplest form of SP, it is limited in its computational burden while giving a "reasonable degree of insight" [27] into the effects of uncertainty on the investment decisions (in that case related to the UK energy system) [27]. Due to the described advantages and challenges, this work uses a two-stage SP approach.

A comprehensive, tutorial-style introduction into the topic of (two-stage) SP is given by Higle [9]. As already mentioned, the uncertain future is often represented by different scenarios or SOWs. In that case, a probability of occurrence must be assigned to each state of the world (SOW) [52]. With a finite number of SOWs and an occurrence probability for each SOW, the two-stage SP problem can be defined as (based on [49,53]).

$$\min_{x \in X} \left\{ g(x) := c^T x + \sum_{k=1}^{K} p_k Q(x, \xi_k) \right\} \tag{2}$$

$$s.t. \quad Ax \le b, \quad x \ge 0 \tag{3}$$

Or formulated as a large linear problem:

$$\min_{x, y_1, \dots, y_k} c^T x + \sum_{k=1}^{K} q_k^T y_k \tag{4}$$

$$s.t. \quad T_k x + W_k y_k \le h_k, \qquad k = 1, \dots, K, \quad x \in X \tag{5}$$

$$Ax \le b, \quad x \ge 0 \tag{6}$$

where:

A: Coefficients of the constraints;
b: Right-hand side of first stage constraints;

c^T: Cost coefficients;
ξ_k $= (q_k, T_k, W_k, h_k)$: Data for the second stage problem of scenario k;
$g(x)$: Objective function;
h: Right-hand side of the second stage constraints;
$k \in \mathbb{N}^K$: Possible future states of the world (K must be a finite number);
p_k: Occurrence probability for scenario k;
$Q(x, \xi_k)$: Optimal solution of the second-stage problem;
$q^T y$: Cost for the recourse action, which is done after the uncertainty resolved (corrective action);
T: Transition matrix for the first-stage variables;
W: Recourse matrix (cost of recourse);
X: Set, defined by a finite number of constraints;
$x \in \mathbb{R}^n$: First-stage decision vector;
$y \in \mathbb{R}^m$: Second-stage decision vector;
y_k: Second stage decision vector for every scenario ξ_k.

At the first stage, the costs $c^T x$ and the "expected cost of the second-stage decision" are minimised [49]. This implies that, at the first stage, a decision regarding the "here-and-now" variable x must be made before the uncertainty ξ resolves. The second stage variables y can be fixed after the uncertainty resolves by obtaining perfect knowledge regarding the uncertain parameters. This makes the second stage a deterministic optimisation problem. By solving the two-stage SP problem, one single solution for the first-stage problem $\tilde{x}$ and a solution for each scenario in the second-stage $\tilde{y}_k$ is found [49]. As already mentioned, the solutions $\tilde{x}$ and $\tilde{y}_k$ are not the optimal result for each scenario, but a robust strategy for each assumed scenario.

The presented two-stage SP method is implemented in DISTRICT. It was proven that the SP version of DISTRICT generates the same results as the deterministic version of DISTRICT by defining a single SOW for the stochastic version and comparing it with the results of the deterministic DISTRICT version (see Appendix A). All optimisation problems were solved with Gurobi [54] and a solve gap of 0.005. The optimisation was limited to the years 2025, 2030, and 2040, as an optimisation of each year between 2022 and 2040 would increase the computational efforts severely without yielding significantly more insight.

2.2. Data and Assumptions

The real-world manufacturing facility, which is used for the scope of this paper, is in the south of Germany. The scope is limited to a single manufacturing facility since the optimisation of an independent facility and its energy system is a typical decision environment in the context of uncertain internal carbon prices, as well as energy carrier costs. The analysed manufacturing site's heat demand is characterised by temperature levels well above 130 °C (up to 750 °C). Some processes and the heating of the buildings require temperature levels of around 75 °C, which allow the limited use of heat pumps. Statistical data on global energy demands suggests that the consideration of the heat demand of buildings is important, as the heating, ventilation, air conditioning, and refrigeration sector is a key-element for a transition to a decarbonised future on a global scale [55]. Due to privacy regulations, the facility's energy demands, pre-installed technologies, and exact location cannot be published. Since no preinstalled technologies are allowed to be communicated, it is assumed that no installations are currently at the facility ("green field"). The PV potential for the facility is estimated based on the available roof and ground areas, with average space demands for ground PV installations (10 m^2 per kW_P [56]). Based on this assumption, the available PV potential is limited to 1634 kW ground-PV and 354 kW flat roof-PV. Additionally, there are loading areas on the premises where PV can be installed in an agrivoltaic style (see [57] for further information on agrivoltaic). The capacity for this type of PV is limited to 176 kW and higher investment costs are assigned to the technology (see Table 1). The PV generation profile is based on the exact location of the facility and retrieved from renewables.ninja [58–60]. The used dataset is MERRA-2 (global) from 2019. Additionally, a tilt of 35° and south-facing (azimuth: 180°) are assumed. The performance ratio is kept at the predefined 0.1. For all other technologies, no capacity limit is set. Table 1 summarises the assumed techno-economic parameters for all technologies that are available to the model.

Table 1. Assumed techno-economic parameters.

Technology Name	Efficiency	Lifetime [a]	Capital Expenditure (CAPEX) $\left[\frac{€}{kW}\right]$	CAPEX in 2040 [Portion of CAPEX (Today)]	Operational Expenditure (OPEX) [Portion of CAPEX]	OPEX $\left[\frac{€}{kW*a}\right]$
LT DAC CCS	0.0005 [61]	20 [61]	730 [61]	0.32 [61]	0.04 [61]	29.2
CHP	0.36 (electric) 0.44 (thermal) [62]	20 [62]	1614 [62]	0.89 [62]	0.03 [62]	48.42
CHP (H_2 ready) [1]	0.36 (electric) 0.44 (thermal)	20	1937	0.89	0.03	58
Electrolyser (mix of different types)	0.65 [62]	26 [62]	738 [62]	0.75 [62]	0.035 [62]	25.83
Gas boiler	0.9 [63]	20 [62]	97 [62]	1 [62]	0.02 [62]	1.9
Gas boiler (H_2 ready) [1]	0.9	20	117	1	0.02	2.3
Heat pump (air)	2.5 [2] [64–66]	20 [62]	900 [62]	0.81 [62]	0.01 [62]	9
Heat pump (soil)	2.5 [2] [65–67]	20 [62]	1656 [62]	0.8 [62]	0.01 [62]	16.56
Hydrogen storage (incl. compressor)	0.95 [62]	30 [62]	163 [62]	1 [62]	0.025 [62]	4
Li-I battery	0.87 [62]	15 [62]	400 [62]	0.31 [62]	0.01 [62]	4
Power-to-heat	0.98 [68]	15 [69]	60 [69]	1	0.016	1.1 [69]
PV (agrivoltaic)	0.175	27	1345	0.71	0.02	26.9
PV (ground)	0.175 [70]	27 [62]	648 [62]	0.71 [62]	0.02 [62]	13
PV (roof)	0.175 [70]	27 [62]	976 [62]	0.61 [62]	0.02 [62]	19.52
Fuel cell CH_4	0.54 (electric) 0.34 (thermal) [62]	20 [62]	9113 [62]	0.16 [62]	0.033 [62]	300
Fuel cell H_2	0.64 (electric) 0.28 (thermal) [62]	20 [62]	8285 [62]	0.16 [62]	0.034 [62]	281.7
Thermal storage	0.7 [71]	40 [72]	400 $\left[\frac{€}{m^3}\right]$ [72]	1 [72]	0.003 [72]	1.2

[1] Investment costs for the H_2-ready technologies are assumed to be 20% higher than natural gas option and the efficiencies are assumed to be similar [73]. [2] Yearly average value. The exact COP of a heat pump is highly dependent on the working environment and the temperature level it is supposed to supply. Therefore, a detailed COP calculation is done in DISTRICT; refer to [74] for further information.

The electricity and heat demand of the facility is assumed to stay constant for the analysed years. The same applies to all energy carrier costs except for hydrogen, which is based on a national energy system analysis for Germany [62]. Table 2 summarises the cost assumptions for the energy carriers. For electricity imports from the grid ("conventional" or "CO_2-neutral"), an additional peak cost of 103 € per kW is included in the optimisation.

Table 2. Energy carrier cost assumptions.

Year	Electricity ("Conventional")		Electricity ("CO_2-Neutral")		Gas		Hydrogen	
	Cost $\left[\frac{€}{kWh}\right]$ [75]	Emissions $\left[\frac{t_{CO_2}}{kWh}\right]$ [76]	Cost $\left[\frac{€}{kWh}\right]$	Emissions $\left[\frac{t_{CO_2}}{kWh}\right]$	Cost $\left[\frac{€}{kWh}\right]$ [77]	Emissions $\left[\frac{t_{CO_2}}{kWh}\right]$ [78]	Cost $\left[\frac{€}{kWh}\right]$ [62]	Emissions $\left[\frac{t_{CO_2}}{kWh}\right]$
2025	0.191	0.000398	0.201 [1]	0	0.0486	0.000202	0.242	0 [2]
2030	0.191	0.000288	0.201	0	0.0486	0.000202	0.213	0
2040	0.191	0.000087	0.201	0	0.0486	0.000202	0.164	0

[1] An additional 0.01€ per kWh is assumed for the CO_2-neutral electricity option [79]. [2] The value is based on the assumption that only CO_2-neutral hydrogen is imported (produced with renewable energy (based on [80]). The local generation of hydrogen is accounted for by the model via electrolysers and hydrogen storage.

As already mentioned in the introduction, future CO_2 prices are highly uncertain and estimates on the "right" price vary significantly (exemplary estimates for CO_2 prices are in [81–84]). For the scope of this work, three possible CO_2 price pathways are defined (Table 3). The aim of the assumed price pathways is to not only align them with regulatory prices, but also to span them across a wide range of possible CO_2 prices. Therefore, the pathways are quite diverse. For a detailed comparison of SP and deterministic optimisation, an additional average price pathway is defined based on the three other pathways. The average pathway is used in the context of the deterministic optimisation in a way that an organisation might not know which of the low, medium, and high price pathway is the most reasonable to optimise the energy system for and just chooses the average for the optimisation, even though it is not assumed to be a real-world scenario.

Table 3. CO_2 price pathway assumptions.

Scenario	CO_2 Price $\left[\frac{€}{t_{CO2}}\right]$		
	2025	2030	2040
Low CO_2 prices [85]	45	72.5	100
Medium CO_2 prices [21]	201	222	264
High CO_2 prices	100	400	600
Average CO_2 prices	115	232	321

To analyse the impact of not only uncertain CO_2 prices, but also uncertain CO_2 prices in combination with different energy carrier costs, the assumptions of Table 3 are expanded and additional SOWs with different energy carrier costs are defined (Table 4).

Table 4. Assumptions for uncertain CO_2 prices as well as energy carrier costs.

Scenario	Year	CO_2 Price $\left[\frac{€}{t_{CO2}}\right]$	Gas Price $\left[\frac{€}{kWh}\right]$	Electricity Conventional/ CO_2-Neutral $\left[\frac{€}{kWh}\right]$	Hydrogen $\left[\frac{€}{kWh}\right]$	Possible Story Line for SOW
SOW_1	2025	45 [85]	0.0486	0.191/0.201	0.242	• Carbon Capture and Storage (CCS) becomes widely available, which reduces the pressure for CO_2-reductions.
	2030	72.5 [85]	0.0486	0.191/0.201	0.213	
	2040	100 [85]	0.0486	0.191/0.201	0.164	• CO_2 prices and gas costs stay rather low since CO_2 can be easily captured by CCS.
SOW_2	2025	201 [21]	0.1	0.241/0.251	0.242	• CO_2 reductions are necessary, and CO_2 prices increase.
	2030	222 [21]	0.1	0.241/0.251	0.19	• Gas production decreases, which increases gas prices. The processes are electrified, which increases the electricity cost.
	2040	264 [21]	0.1	0.241/0.251	0.12	• The hydrogen costs decrease faster (e.g., hydrogen imports) as efforts are increased to find a substitution for gas.
SOW_3	2025	100	0.0972	0.191/0.201	0.242	• The electricity generation is increased (e.g., more renewable generation) and processes are electrified.
	2030	400	0.0972	0.191/0.201	0.213	
	2040	600	0.0972	0.191/0.201	0.164	• The hydrogen costs do not decrease (e.g., only limited imports) and gas is substituted where possible.
SOW_average	2025	115	0.0819	0.2077/0.2177	0.242	• Average from the above-described SOWs. As already mentioned, just for deterministic optimisation purposes.
	2030	232	0.0819	0.2077/0.2177	0.2053	
	2040	321	0.0819	0.2077/0.2177	0.1493	

2.3. Result Comparison Process

To analyse the impact of uncertain CO_2 prices as well as energy carrier costs on the solutions of deterministic optimisation and SP, a result generation and comparison process is defined. For a detailed analysis of the impact that uncertain CO_2 prices as well as energy carrier costs have, two separate optimisation environments are defined. First, scenarios where only uncertain CO_2 prices exist are analysed (based on Table 3, results in Section 3.1). Second, scenarios where both CO_2 prices and the energy carrier cost deviate are analysed (based on Table 4, results in Section 3.2).

For the scenarios where only the CO_2 prices are uncertain, four deterministic and four SP optimisation problems are defined. Figure 3 illustrates the defined scenarios.

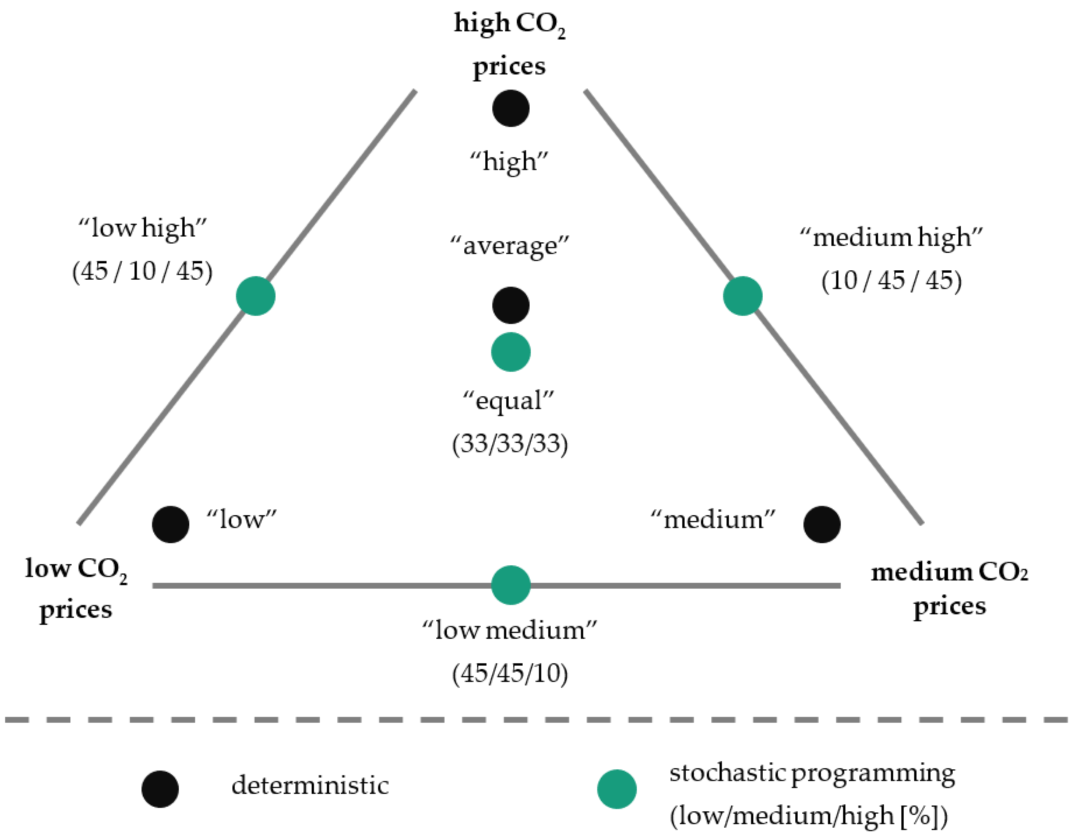


Figure 3. Defined scenarios with uncertain CO_2 prices.

As already mentioned, the scenario probability of the SP scenarios must be specified exogenously [27], even though no information on the occurrence probability exists. One option is to equally weight the probability for each scenario, known as the Laplace criterion, which is the "discrete equivalent of a continuous uniform distribution" [27,86]. This results in a roughly 33% chance for each of the assumed scenarios (referred to as "equal" in Figure 3). To investigate the possible range of probability assumptions and its effects, three SP scenarios are spread evenly between the assumed price pathways (referred to as "low high", "low medium", "medium high"). The numbers below the stochastic scenarios indicate the occurrence probability for each CO_2 price pathway. The presented setup is the same for the scenarios where the CO_2 prices and energy carrier costs are uncertain (Figure 4).

For a comprehensive analysis, three different optimisation approaches are compared. First, myopic optimisation is used, where the analysed years are optimised independently from one another. The method is further split into "myopic" and "myopic_years" for the scope of this paper. In the "myopic" approach, not only is each year optimised independently from the others, but it is also assumed that there exist no preinstalled technologies ("green field"). With the "myopic_years" approach, each year is optimised independently from the others. However, technologies that are installed in previous years and have not surpassed their lifetime can be used by the optimisation model. The third approach is perfect foresight, where all analysed years are optimised at once and technologies that are installed in previous years and have not surpassed their lifetime are considered. Table 5 summarises the optimisation approaches.

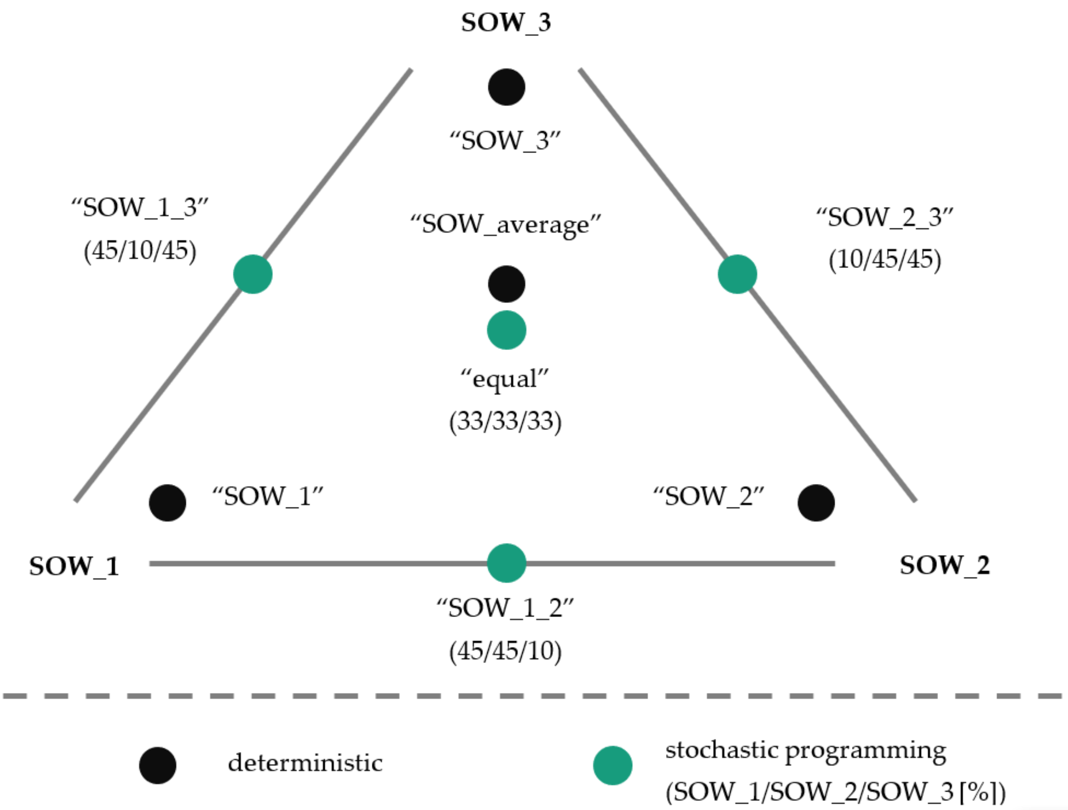


Figure 4. Defined scenarios with uncertain CO_2 prices as well as energy carrier costs.

Table 5. Overview on the optimisation approaches.

Name for the Scope of This Work	Optimisation Method	Short Description of Optimisation Approach
Det_myopic	Deterministic	Each year (2025, 2030, 2040) is optimised independently from the others. For all years, a "green field" is assumed.
Sto_myopic	Stochastic programming	
Det_myopic_years	Deterministic	Each year is optimised independently from the others, but technologies that are installed in earlier years are considered by the model if they have not surpassed their lifetime.
Sto_myopic_years	Stochastic programming	
Det_perfect_foresight	Deterministic	All considered years are optimised at once. Technologies that are installed in earlier years are considered if they have not surpassed their lifetime.
Sto_perfect_foresight	Stochastic programming	

To evaluate the performance of the different optimisation approaches, once the underlying assumptions change and after the investments are done, a predefined procedure is used. Each scenario is optimised with the different optimisation approaches and according to its underlying assumptions; e.g., the low CO_2 price scenario is optimised with "myopic" optimisation. The optimised installation pathway is then used to analyse what happens if the medium or high CO_2 price pathway manifests. With this procedure, the potential additional costs for each scenario can be calculated. Figure 5 summarises the processes for the scenarios where only the CO_2 prices are uncertain. Figure 6 summarises the processes for the scenarios where the CO_2 prices and energy carrier cost are uncertain.

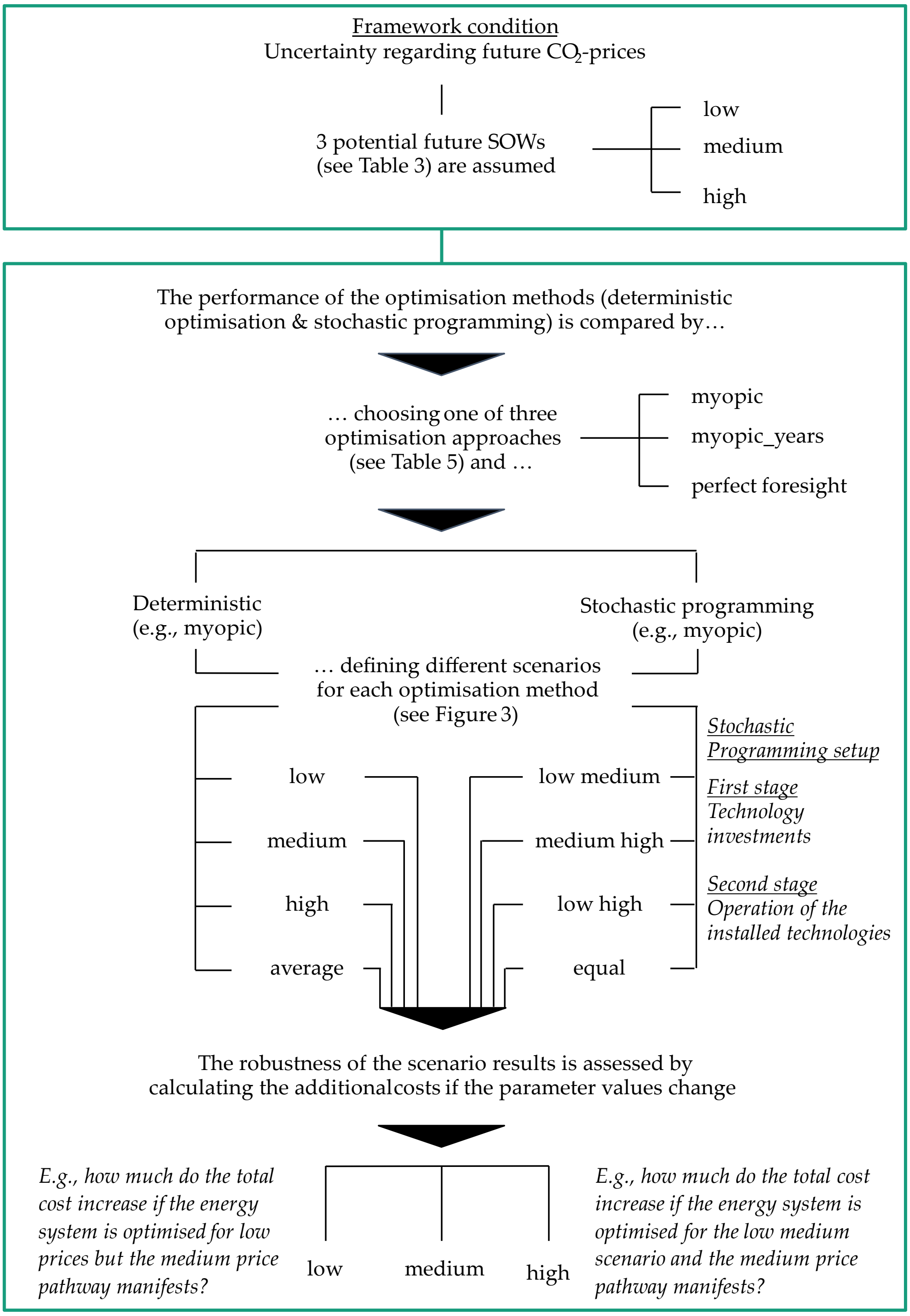


Figure 5. Process to compare the optimisation results (uncertain CO_2 prices).

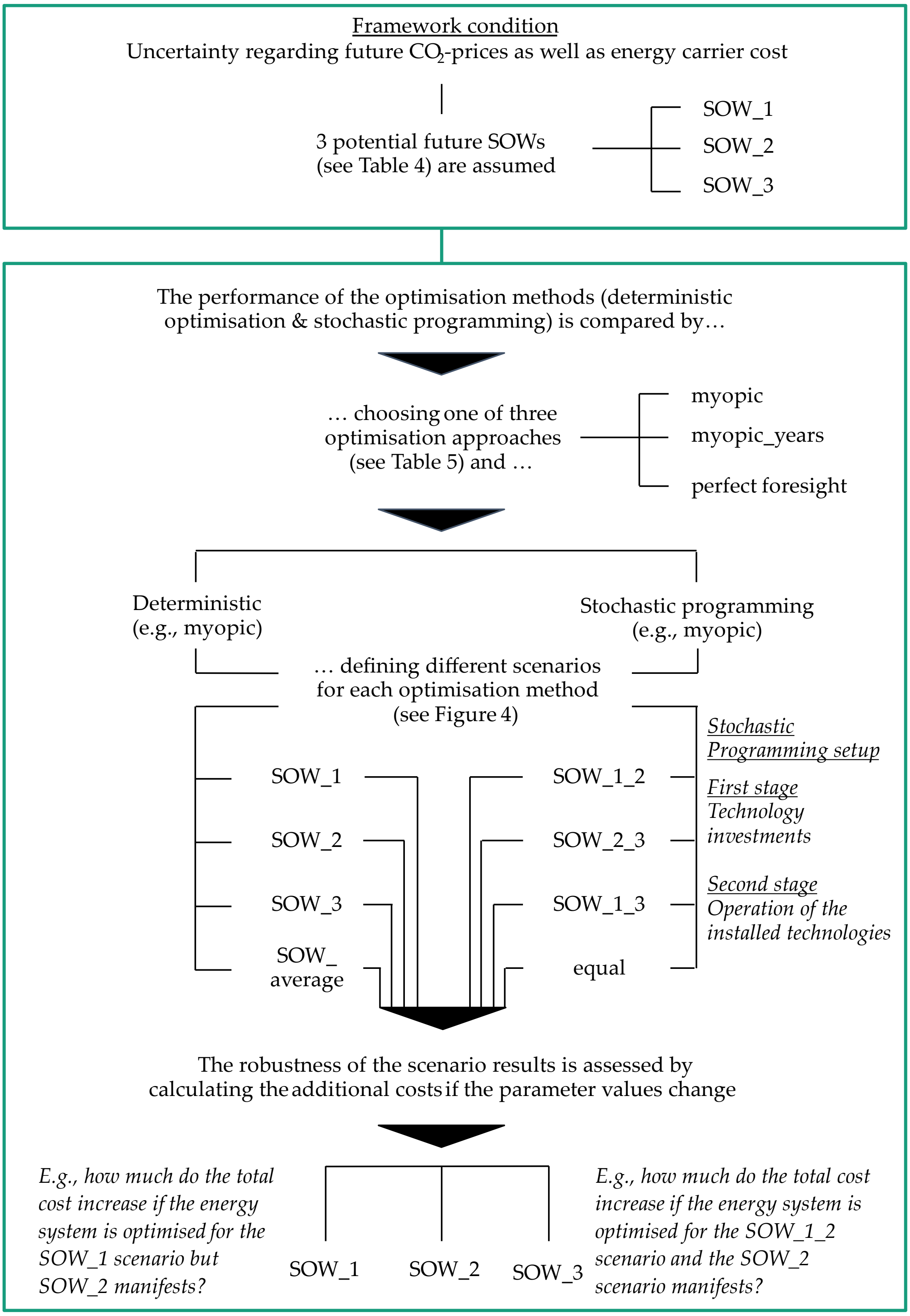


Figure 6. Process to compare the optimisation results (uncertain CO_2 prices and energy carrier cost).

It should be noted that the result comparison process leads to the deterministic solutions not having any cost deviations for the cases where the assumed future manifests (e.g., the energy system is prepared for SOW_1 and SOW_1), as this is the optimal solution. One the other hand, the stochastic solutions have cost deviations for all scenarios, as SP does not yield an optimal solution for specific scenarios, but a robust solution across all defined scenarios.

3. Results

The results section is divided into two parts, in line with the two different uncertainty frameworks that are defined for this work. In Section 3.1, the results of the scenarios with uncertain CO_2 prices are examined (based on Table 3). In Section 3.2, the results of the scenarios with uncertain CO_2 prices and uncertain energy carrier costs are analysed (based on Table 4).

3.1. Scenarios with Uncertain CO_2 Prices

First, the results of the myopic optimisation (Det_myopic and Sto_myopic) are examined regarding their robustness in the environment of uncertain CO_2 prices. Figure 7 shows the total percentage cost deviation for each solution in relation to the optimal scenario solution.

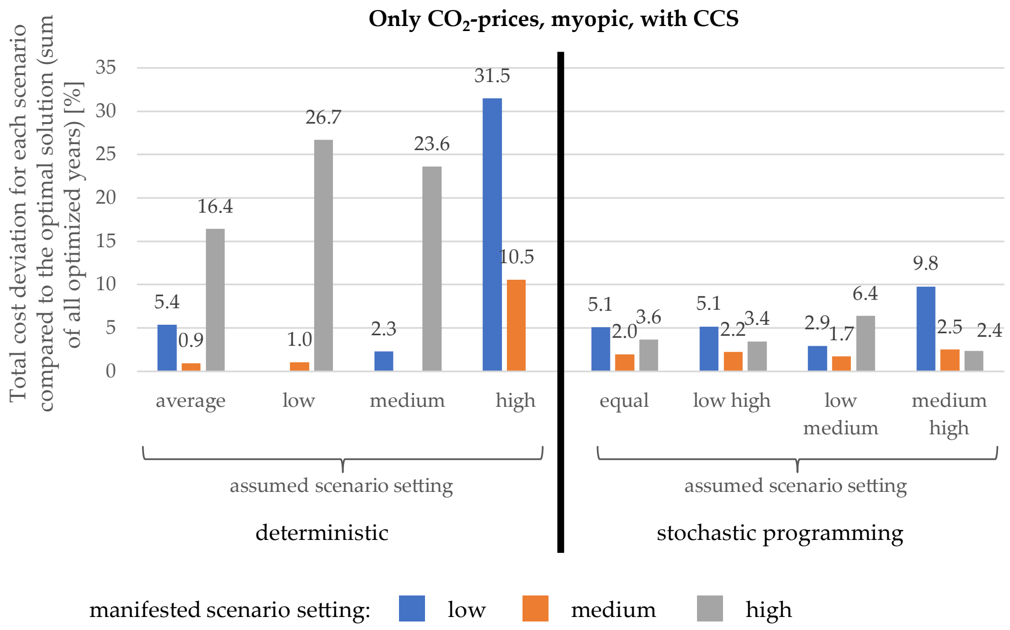


Figure 7. Total cost deviation per scenario compared to the optimal solution for uncertain CO_2 prices (myopic, with CCS).

For a better understanding, the low category (*y*-axis) is explained in detail. As mentioned in Section 2.2, low refers to an optimisation under the assumption that the low CO_2 price pathway will occur (see Table 3 and Figure 3). The bars in the low category of Figure 7 indicate the cost deviation if the energy system is optimised for the low assumption, but, after the investment decision is made, the medium or high CO_2 price pathway manifests. If the system is optimised for the low pathway, but the high pathway manifests, the total system cost is 26.7% higher than the system cost of the optimal high solution. The same applies to all other scenarios presented in Figure 7.

A better overview on the cost deviation of each scenario is given by the summed total cost deviation (STCD), which is presented in Figure 8. The STCD is the sum of the total cost deviation for each scenario (presented in Figure 7).

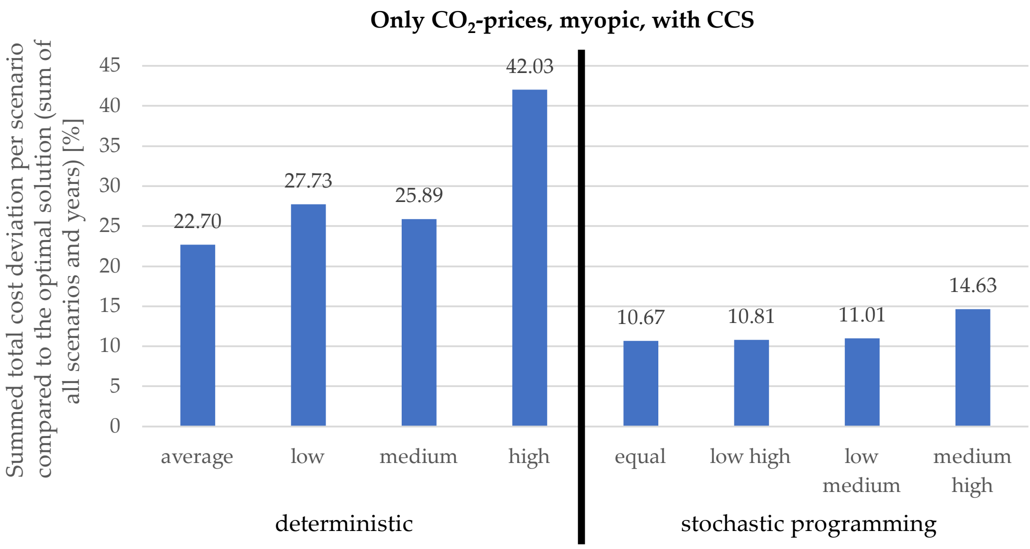


Figure 8. STCD per scenario for uncertain CO_2 prices (myopic, with CCS).

Figure 8 shows a substantial difference between the STCD of the deterministic and the SP solutions. All SP scenarios have significantly lower STCDs, which underline their higher robustness to changes in the CO_2 prices. The robustness depends on the installed technologies. Figure 9 shows the installed technologies for the average, low, medium, high, equal, and medium-high scenarios.

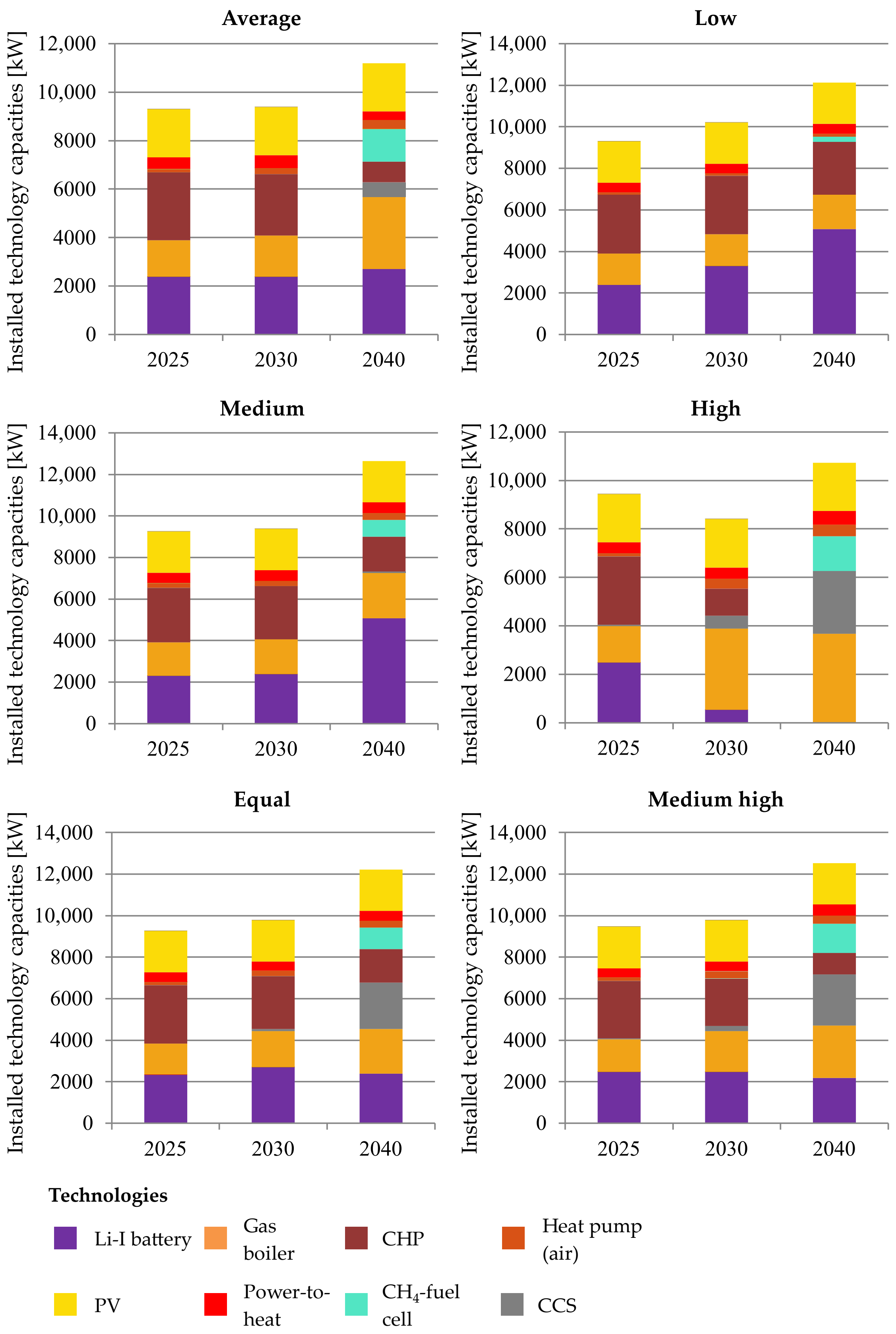
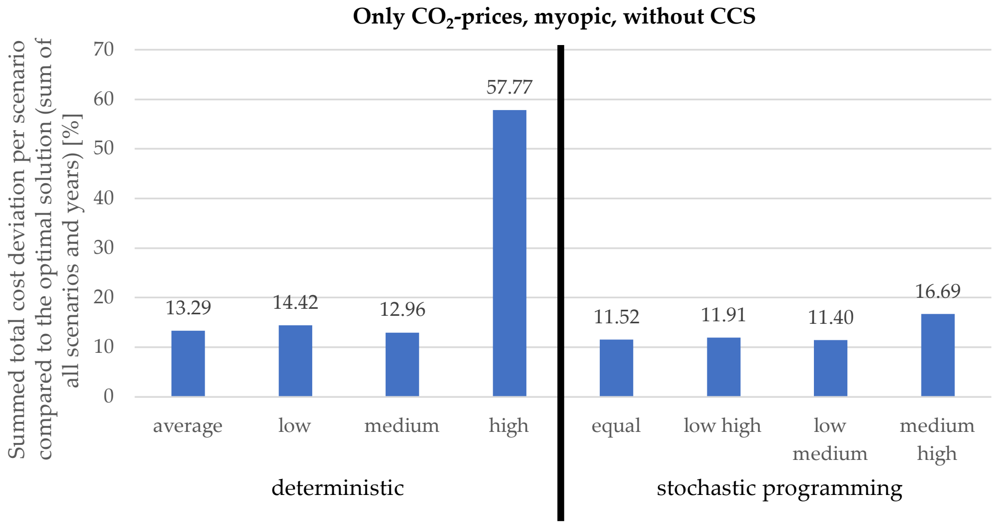


Figure 9. Installed technologies for different scenarios with uncertain CO_2 prices (myopic, with CCS).

Figure 9 underlines two main aspects. First, SP finds a solution that none of the deterministic scenarios do. With this solution, the energy system can react flexibly to changing CO_2 prices. Second, the CCS technology plays a crucial role, especially in the average and high price, as well as in the SP scenarios. The important role of CCS in the high price scenario also explains the cost increase for the cases where low or medium prices are assumed, but the high price pathway manifests. The total cost for these scenarios increases by 26.7% and 23.6%, respectively (see Figure 7), which is mainly due to the missing CCS technology. The high price scenario has a similar dependency since heat generation builds around gas boilers as well as CH_4 fuel cells, and the associated emissions are compensated with CCS. However, when but low or medium prices manifest, the system cost increases by 31.5% and 10.5%, respectively (Figure 7), since the system cannot use CHP, which is used in the energy system optimised for low and medium scenarios.

Overall, the results indicate that, beside SP yielding robust solutions, the different CO_2 prices lead to path dependencies in the installed technologies, especially for CCS. However, the low temperature direct air capture (LT DAC) CCS technology, which is assumed for this work, is currently not commercially available in small scale applications (technology readiness level below 9) [87,88]. Furthermore, it is debateable how many CO_2 storage opportunities a real-world facility has. Therefore, additional optimisations are done where CCS is not available as a technology option. Figure 10a shows the STCD for these scenarios.

Graphic (a)



Graphic (b)

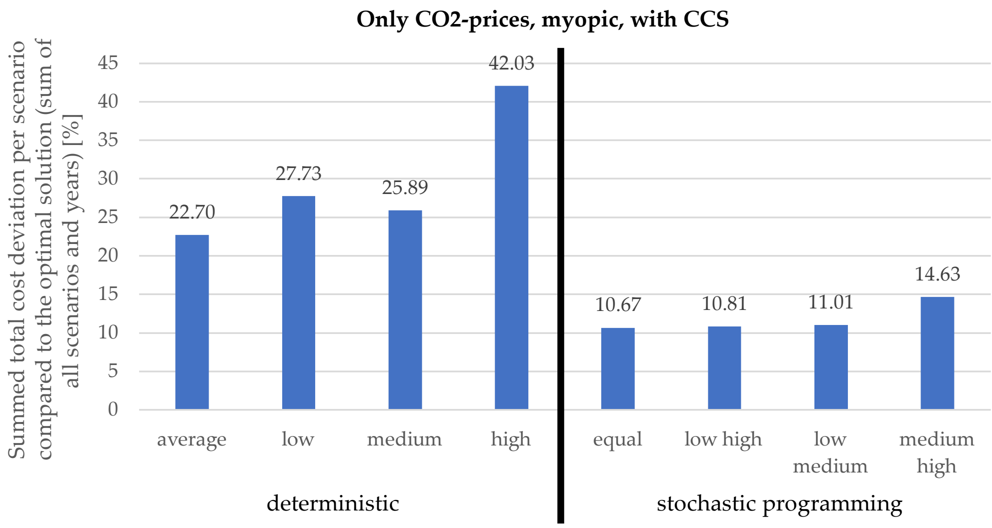


Figure 10. (**a**) STCD per scenario for uncertain CO_2 prices (myopic, without CCS); (**b**) STCD per scenario for uncertain CO_2 prices (myopic, with CCS).

Comparing the STCDs for the scenarios with and without CCS (Figure 10a,b), shows lower STCDs for most of the deterministic scenarios, except for the high one. Leaving the STCD of the high scenario aside, the difference between the STCD of the deterministic and SP solutions is notable, but not as high as in Graphic (b). Again, the installed technologies explain the STCD differences. Figure 11 shows the installed technologies for the low, medium, high, and equal scenarios.

Figure 11. Installed technologies for different scenarios (myopic, without CCS).

The significant cost deviation of the high scenario is explainable by the technology switch from gas to hydrogen and the missing CHP in 2040, which reduces the flexibility of the energy system in the high scenario. Figure 12 illustrates the missing flexibility by displaying the energy generation and system cost of the low scenario and the scenario optimised for the high price pathway, but with low CO_2 prices ("planned for high but low manifests").

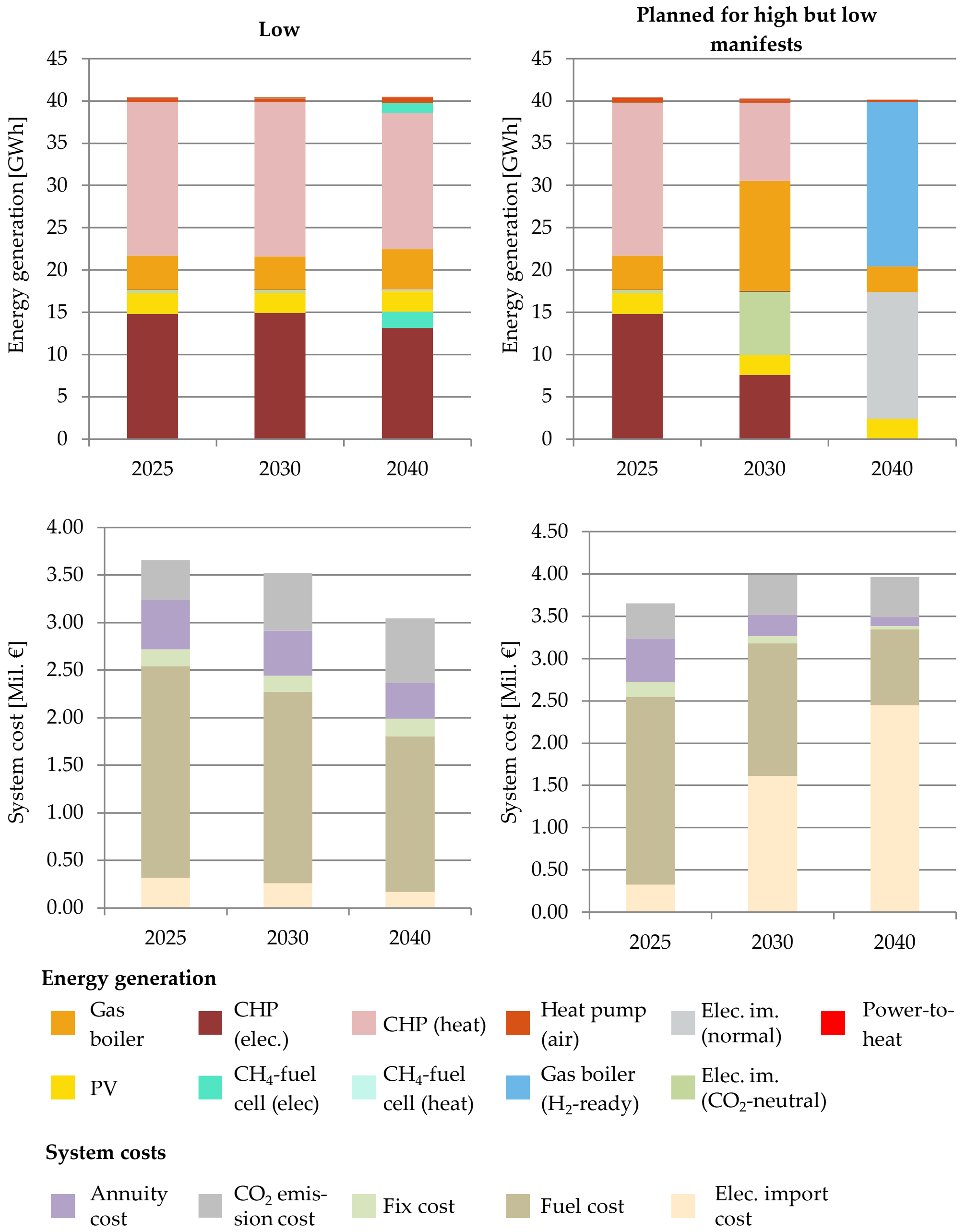


Figure 12. Energy generation and costs for the low and "planned for high but low manifests" scenarios (myopic, without CCS).

The low scenario results show the optimal and therefore cheapest solution, which builds around the use of CHP to meet most of the electricity and heat demand. The system, which is optimised for the high pathway, does not have this option, and must use the boiler to meet the heat demand while electricity is imported. Therefore, the total cost is higher compared to the low scenario (3.96 million € vs. 3.05 million € in 2040). Figure 13 shows the energy generation and cost structure for the equal scenario, in case of low CO_2 prices. The system is, due to the installed technologies (see Figure 11), more flexible and can react to the low CO_2 prices by, at least in part, using CHP.

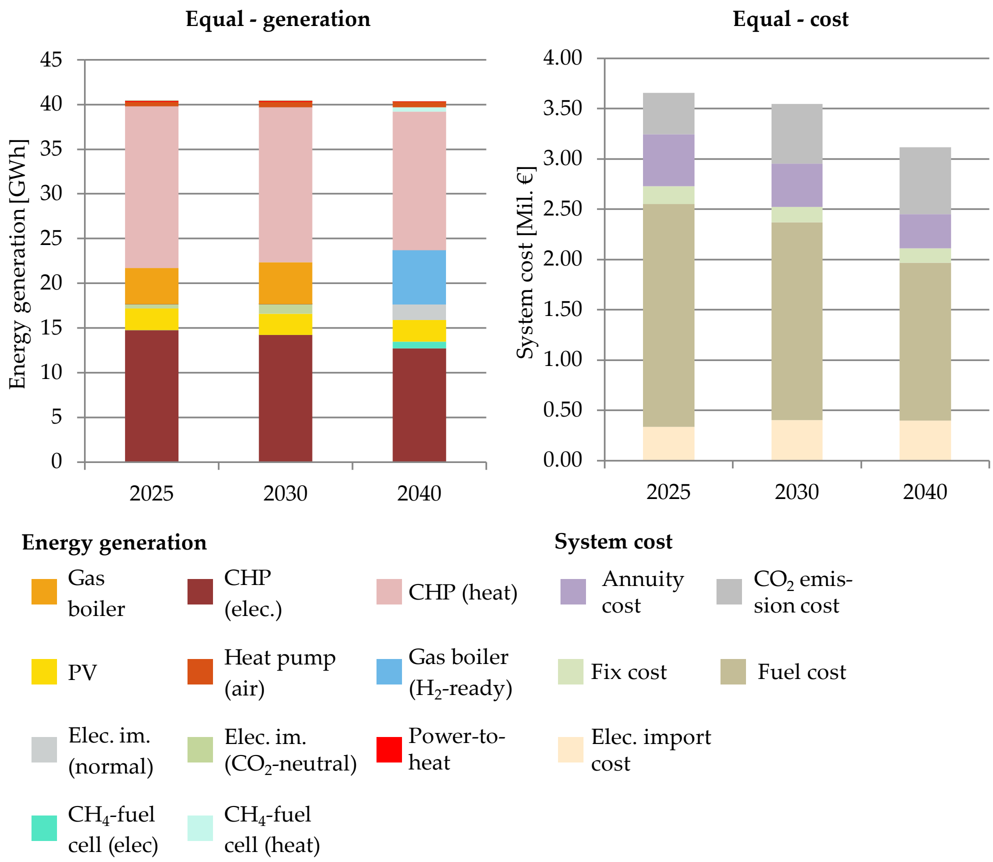


Figure 13. Energy generation and costs for the equal scenario (myopic, without CCS).

The significantly lower STCD of the low and medium scenarios, once CCS is excluded, can be best explained by looking at the cost structure of the high and "planned for high but low manifests" scenario for both settings (with and without CCS, Figure 14). The cost structure shows that the cost of the "planned for high but low manifests" scenario does not change, since the installed technologies do not change either (see Figures 9 and 11). The cost of the high scenario increases due to the missing CCS technology and the switch to hydrogen. Therefore, the STCD, which is a relative measure, decreases for the low and medium scenarios once CCS is excluded.

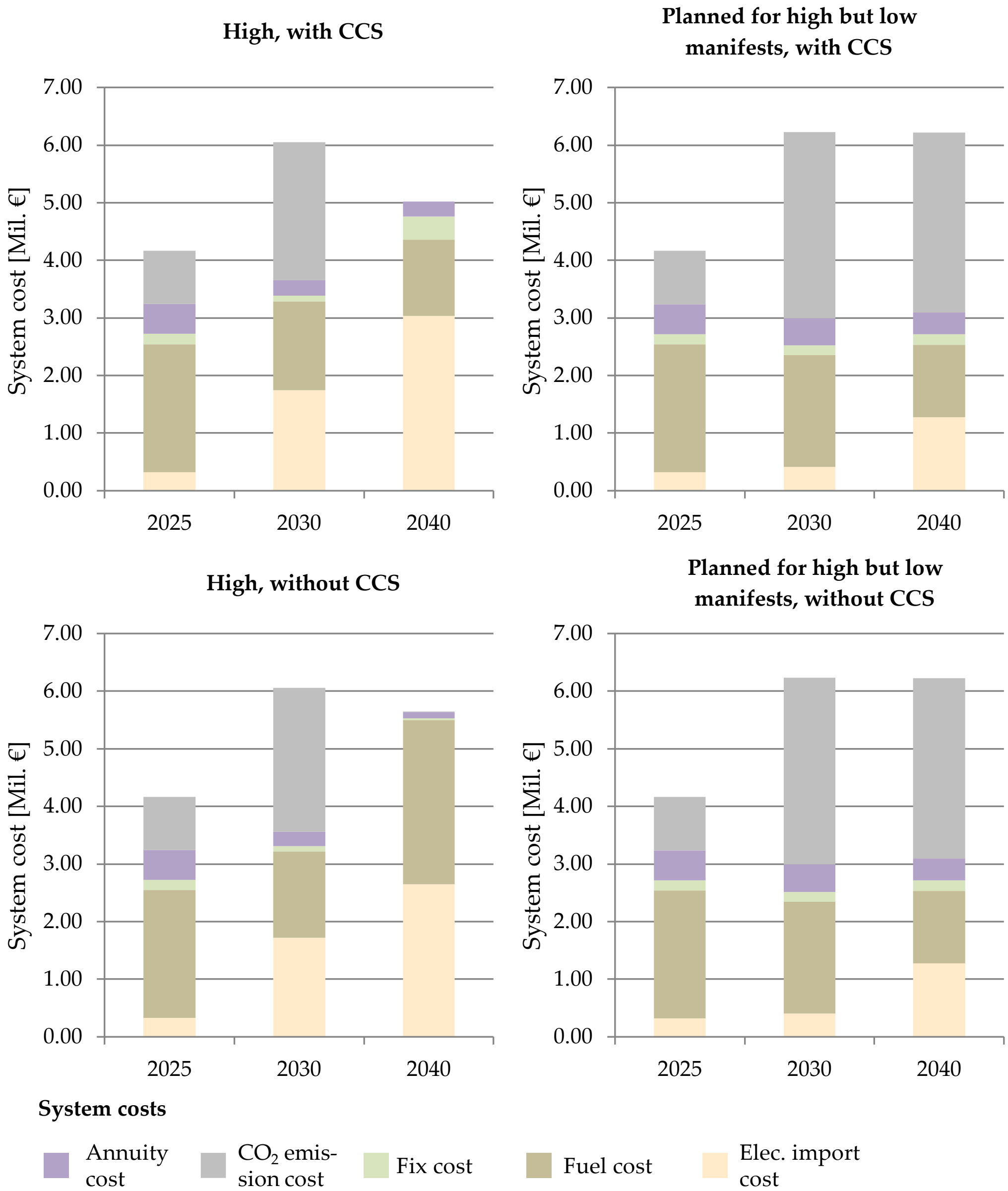
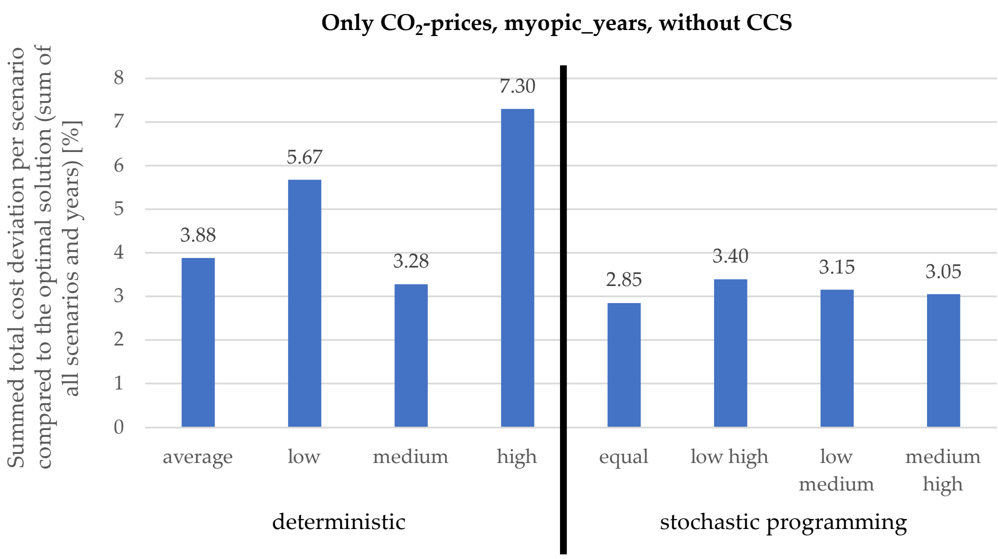


Figure 14. Cost structure of the high and "planned for high but low manifests" scenarios (myopic, with and without CCS).

Since the STCD of the deterministic and SP scenarios is similar for the cases where CCS is excluded, the analysis of the other optimisation settings (Table 5) is focused on the scenarios without CCS. The main reason, beside the debateable availability of CO_2 storage opportunities at the real-world facility, is that for this scenario setting, SP might not yield a significant advantage, which should be further investigated. Figure 15a shows the STCD for the Det_myopic_years and Sto_myopic_years scenario results. Here, technologies that were installed in previous years are available to the model if they have not surpassed their lifetime (Table 5).

Graphic (a)



Graphic (b)

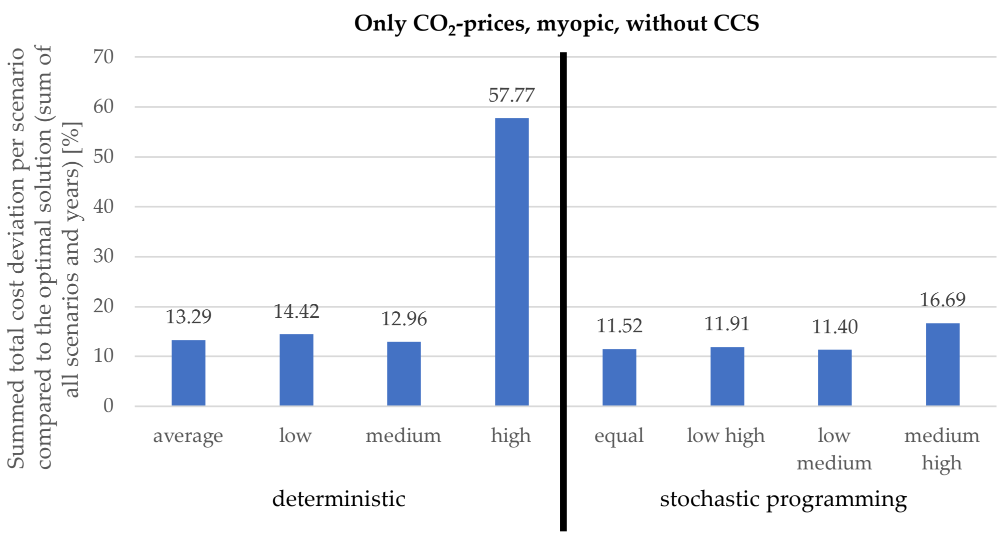


Figure 15. (**a**) STCD per scenario for uncertain CO_2 prices (myopic_years, without CCS); (**b**) STCD per scenario for uncertain CO_2 prices (myopic, without CCS).

The comparison of the myopic_years and the myopic results (Figure 15a,b) shows that the STCD is significantly lower across all myopic_years scenarios. The reason for the lower STCD is explainable once the high scenario of this setting (Figure 16) is compared with the one from the Det_myopic setting (Figure 11).

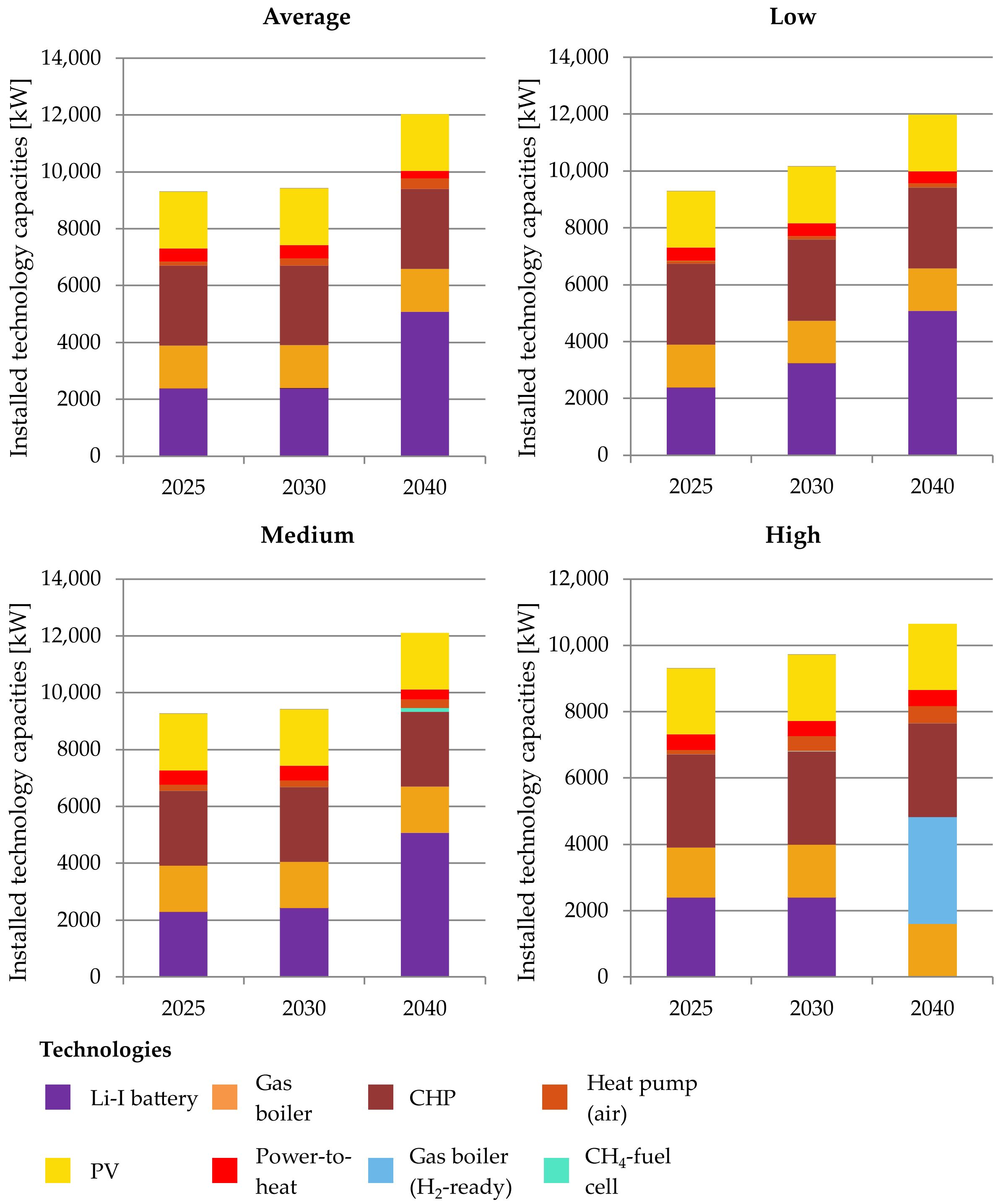


Figure 16. Installed technologies for different scenarios (myopic_years, without CCS).

Figure 16 shows that the CHP is still available in the high scenario in 2040, as it has not surpassed its lifetime. However, in the high scenario, the CHP is used only in a very limited way in 2040, as Figure 17 underlines. Therefore, the CHP has a significant overcapacity in 2040 for the high price scenario.

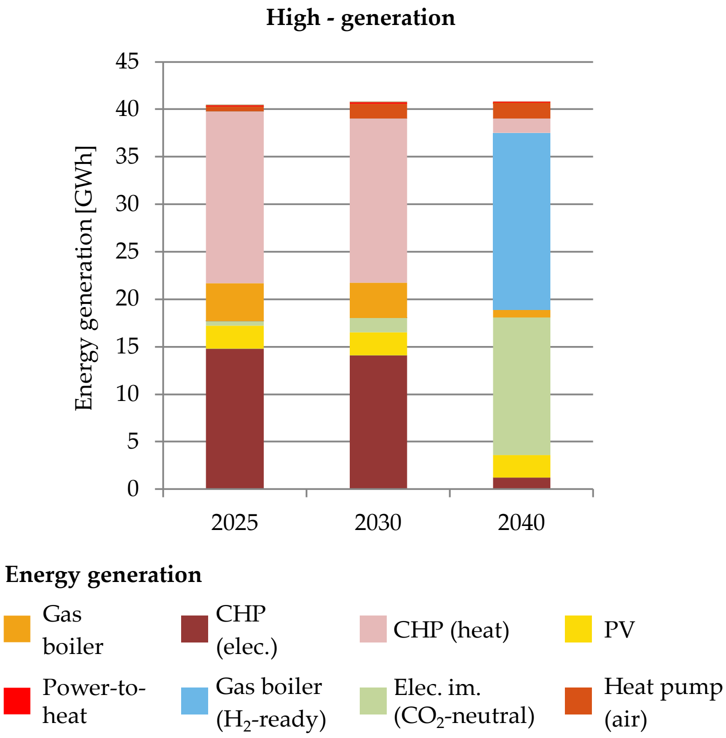


Figure 17. Energy generation for the high scenario (myopic_years, without CCS).

It should be noted that the overcapacity in the myopic_years setting is due to the assumption that the installed technologies stay available if they have not surpassed their lifetime, which is at least debateable. "Stay available" means that the technologies are not decommissioned once they are not planned to be used anymore or other technologies are installed. Usually, organisations have limited space available and decommission technologies that they do not plan to use in the future. Figuratively speaking, organisations often do not have several different (redundant) heating technologies installed within one facility (excluding security-related cases for emergency reasons). Decisions that build on this optimisation setting might generate the impression of robust solutions, even though the robustness originates from the assumption that past investments are still available to the system.

Due to the CHP overcapacity in 2040, the system has more flexibility in choosing which technology to use. If the low pathway manifests, even though the model is optimised for high CO_2 prices, it can still use the CHP. With the option to switch back to CHP, the cost deviation is reduced. If Figures 11 and 16 are compared, it is also visible that the energy systems of the low and medium scenarios do not deviate that much. The lower STCD for the low and medium scenarios of the myopic_years setting is mainly due to the higher investment cost of the high scenario. In other words, the low and medium scenarios are, again, not significantly cheaper for the myopic_years setting, but the high scenario is more expensive.

Figure 18 shows the STCD for the scenarios that are optimised with the method of perfect foresight. The pattern is similar to the Det_myopic and Sto_myopic scenario setting pattern, but the deviation height is more comparable to the Det_myopic_years and Sto_myopic_years setting. The small summed total cost deviation can be explained by the availability of previously-installed technologies, which increases the flexibility of the energy system, as in the myopic_years scenarios. However, as all years are optimised at once, the cost deviation pattern is more similar to the one from the myopic setting, where each year is optimised separately, and the energy system design can be better aligned with the energy system environment. Overall, the previously-discussed findings (e.g., availability of previously-installed technologies, CCS, and path dependencies) are also applicable to this optimisation approach.

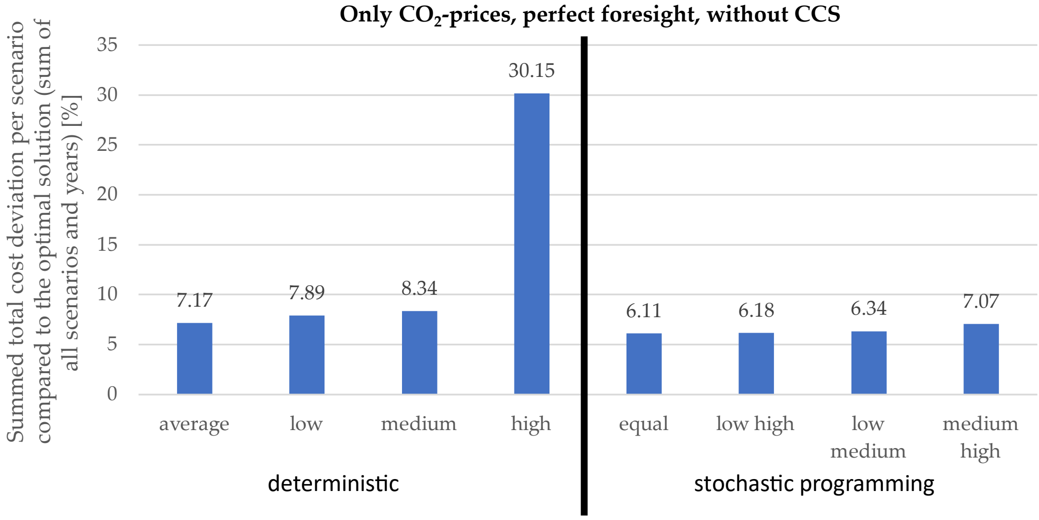


Figure 18. STCD per scenario for uncertain CO_2 prices (perfect foresight, without CCS).

Interim Conclusion

First, the results of Section 3.1 show the low robustness of the deterministic scenarios (high STCDs) for scenarios where path dependencies occur. The path dependencies arise for the scenarios where CCS is available and for the high scenario (without CCS) where a switch to the hydrogen boiler is made. For all optimisation approaches, the SP yields more robust solutions, especially for the scenarios with path dependencies. The path dependency is due to the available technology options (CCS). As already mentioned in the introduction, the factors in the context of energy systems are highly intertwined. Therefore, analysing solely the impact of CO_2 prices on an energy system without taking the broader energy system environment into account may be short-sighted. Consequently, the analysis of this work is expanded in Section 3.2 by assuming uncertain CO_2 prices as well as energy carrier costs to analyse if the advantages of SP are proven not only in the context of path dependencies due to technology options, but also due to (cost) factors such as energy carrier costs.

Second, an organisation should be aware of the underlying assumptions that come with certain optimisation approaches. The already-discussed use of previously-installed technologies (myopic_years, perfect foresight) should be treated with caution. Organisations usually decommission unused technologies and do not have high overcapacities with different generation technologies to maintain them over several years. Analysing the sensitivity of optimisation results, based on this setting, might lead to the deluded conclusion of robustness based on the seemingly low STCD if the underlying assumptions are not carefully considered.

Third, when looking at the STCDs, the conclusion should not be that the only mistake is to assume high CO_2 prices, as there the STCD is maximal. The cost deviations of the average, low, and medium scenarios exceed 10%, which might lead to uncatchable competitive disadvantages. The danger of CO_2 price assumptions that are too low in the broader energy system context is additionally underlined in the next section.

3.2. Scenarios with Uncertain CO_2 Prices and Energy Carrier Costs

The results of this section are based on the assumptions presented in Table 4. For a consistent result analysis of Sections 3.1 and 3.2, the STCD for the Det_myopic and Stro_myopic scenarios with CCS are presented first (Figure 19a).

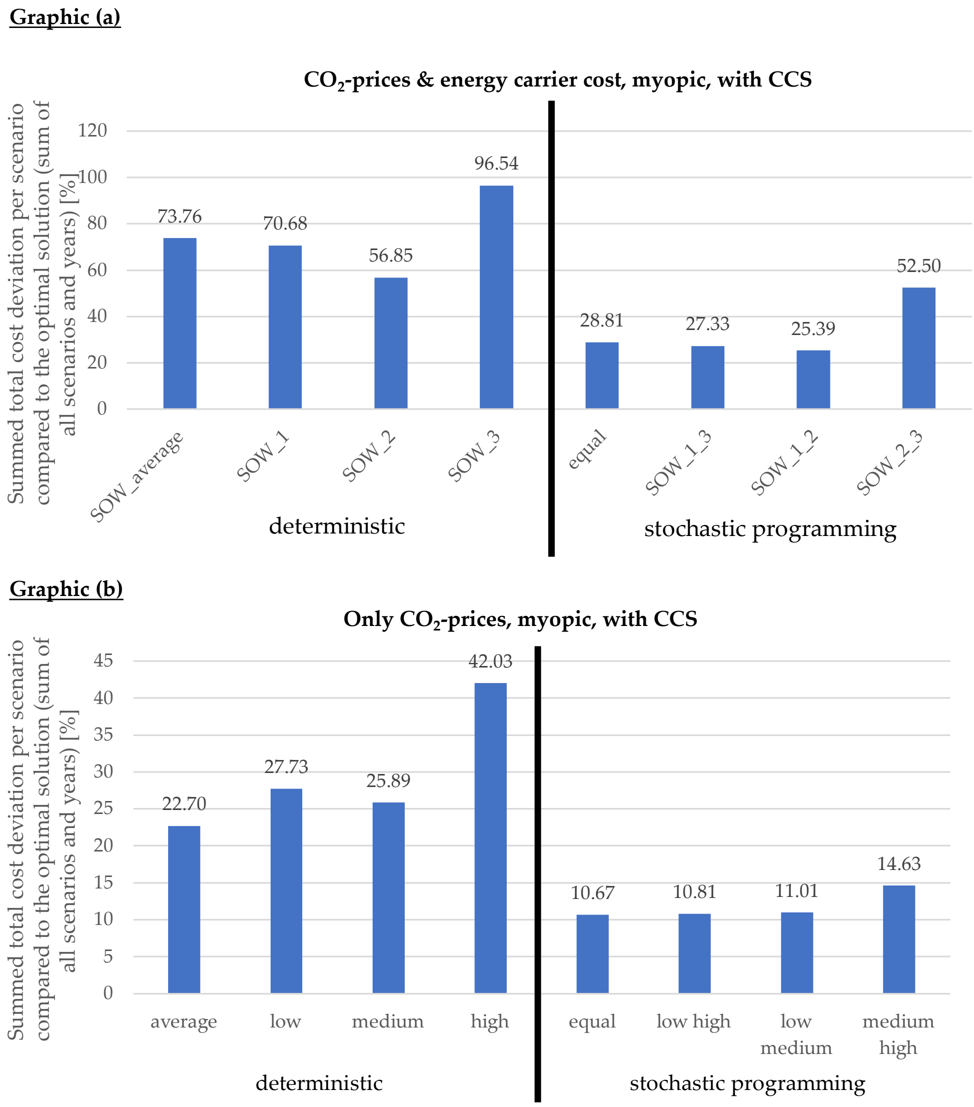


Figure 19. (**a**) STCD per scenario for uncertain CO_2 prices and energy carrier cost (myopic, with CCS); (**b**) STCD per scenario for uncertain CO_2 prices (myopic, with CCS).

The comparison of Figure 19a,b shows significantly higher STCDs across all scenarios that exceeds 56% for the deterministic scenarios. Again, the STCD difference between the deterministic and SP solutions underlines the strong robustness of the latter (lower STCDs of the SP solutions compared to the deterministic ones). This finding also holds for the scenarios where CCS is excluded (Figure 20). In contrast to the results of Section 3.1, the STCDs are very similar for the scenarios with and without CCS (compare Figure 20a,b).

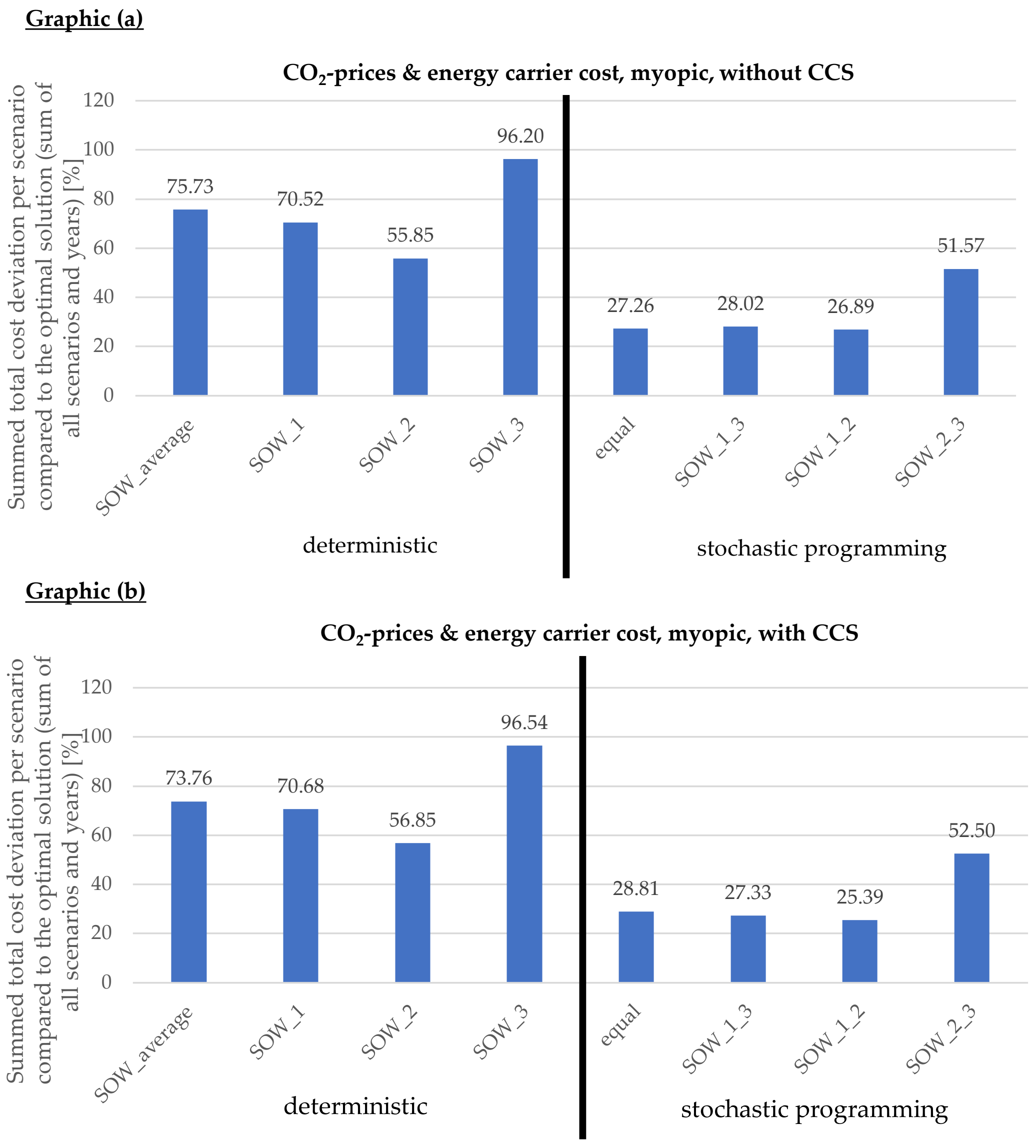


Figure 20. (**a**) STCD per scenario for uncertain CO_2 prices and energy carrier cost (myopic, without CCS); (**b**) STCD per scenario for uncertain CO_2 prices and energy carrier cost (myopic, with CCS).

The high deviation of the STCDs, independent from the availability of CCS, can be explained by the diverse structure of the optimal energy system for each deterministic scenario, which leads to strong path dependencies. Figure 21 shows the installed technologies for the average, low, medium, high, equal, and medium-high scenarios. Again, the SP solution is different from all deterministic solutions. this underlines that, even with the simple two-stage SP, SP already allows insight that is not retrievable by deterministic scenario settings.

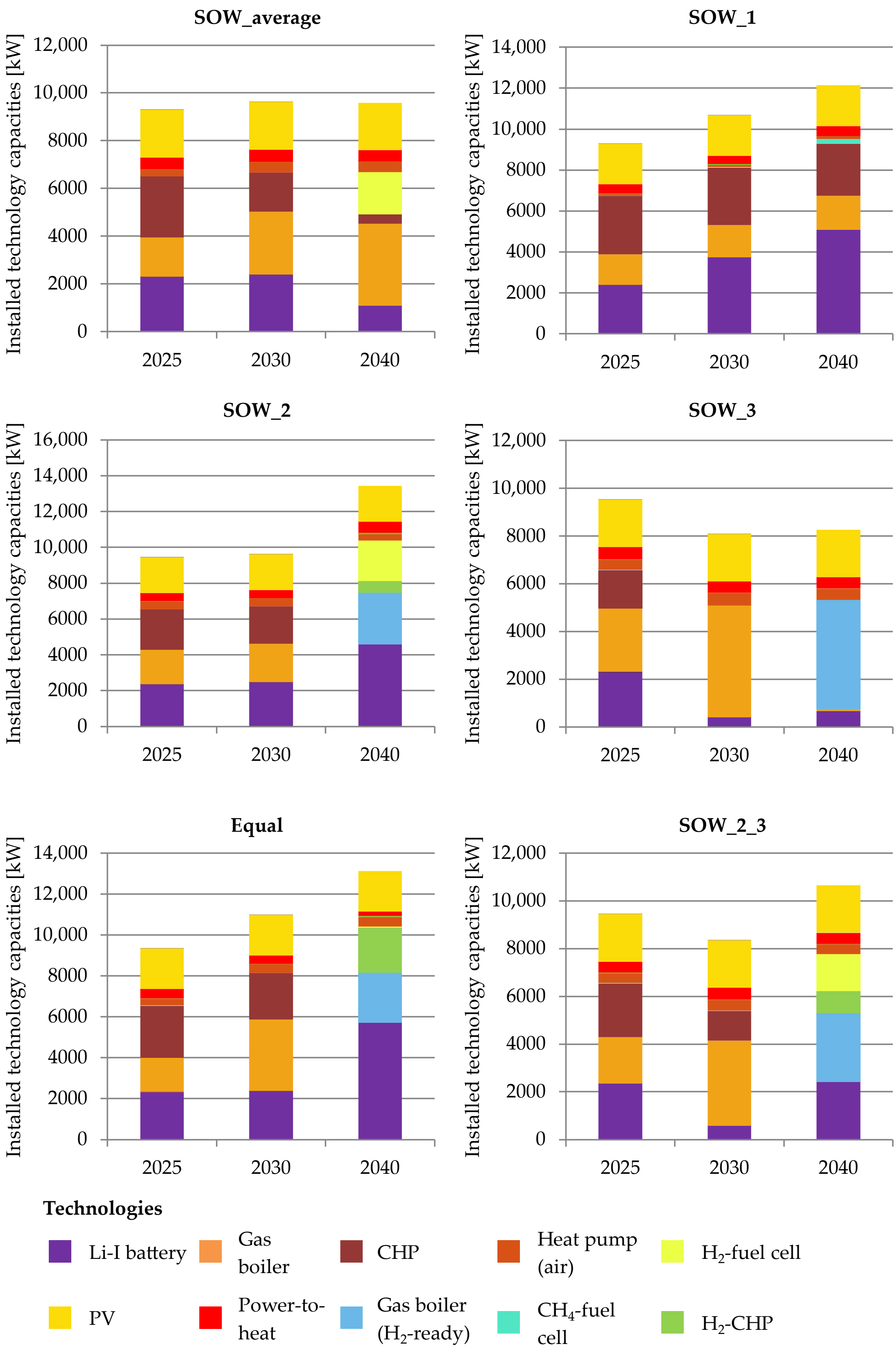


Figure 21. Installed technologies for different myopic scenarios (myopic, without CCS).

If the installed technologies of Figure 21 are compared with the installed technologies of the scenarios with the option for CCS (Appendix B), it is visible that CCS does not play an important role. Each scenario, independent of the availability of CCS, builds around another predominant energy system structure (Figure 21 and Appendix B) and use (Appendix C), which is the reason for the strong path dependencies. The SOW_1 scenario continues to use CHP, fuelled by gas, while the SOW_2 scenario uses hydrogen-ready fuel cells and boilers. For the SOW_3 scenario, the energy system imports electricity and uses hydrogen-ready boilers to meet the heat demand. Since the path dependencies arise not only due to the different CO_2 prices, but also due to the energy carrier cost, the importance of CCS is limited. Together with the short discussion on CCS in Section 3.1, which questions the availability of sufficient onsite CO_2-storage opportunities, the rest of this section will also focus on the scenarios where CCS is not available to the model.

The STCDs of the Det_myopic_years and Sto_myopic_years scenarios (Figure 22) have a similar pattern as the scenarios in Section 3.1. The STCD is less than in the Det_myopic and Sto_myopic scenarios, but contrast to the results of Section 3.1, the deviation is still very high. Again, the SP solutions are noticeably more robust.

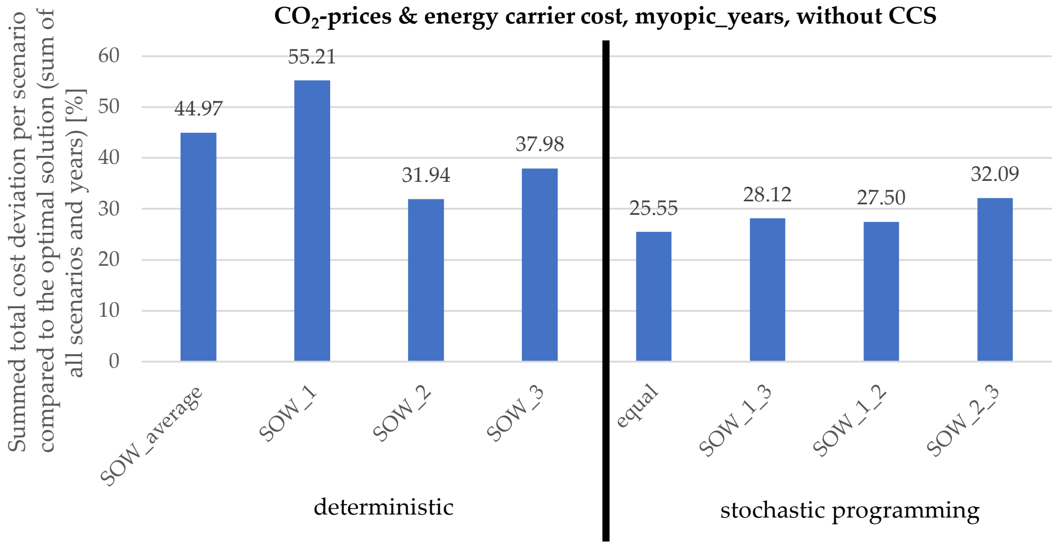


Figure 22. STCD per scenario for uncertain CO_2 prices and energy carrier cost (myopic_years, without CCS).

The lower STCD is, as already mentioned in Section 3.1, mainly due to the previously-installed technologies and thus overcapacities, giving the energy system a higher flexibility (as seen in Figure 17). Comparing the installed capacities for the high scenario of the myopic and myopic_years solutions (Figures 21 and 23) underlines the argument, since CHP is still available to the model in the myopic_years case, but not the myopic case. This allows a switch in energy generation technologies if, for example, the low-price pathway manifests (as already seen in Section 3.1)

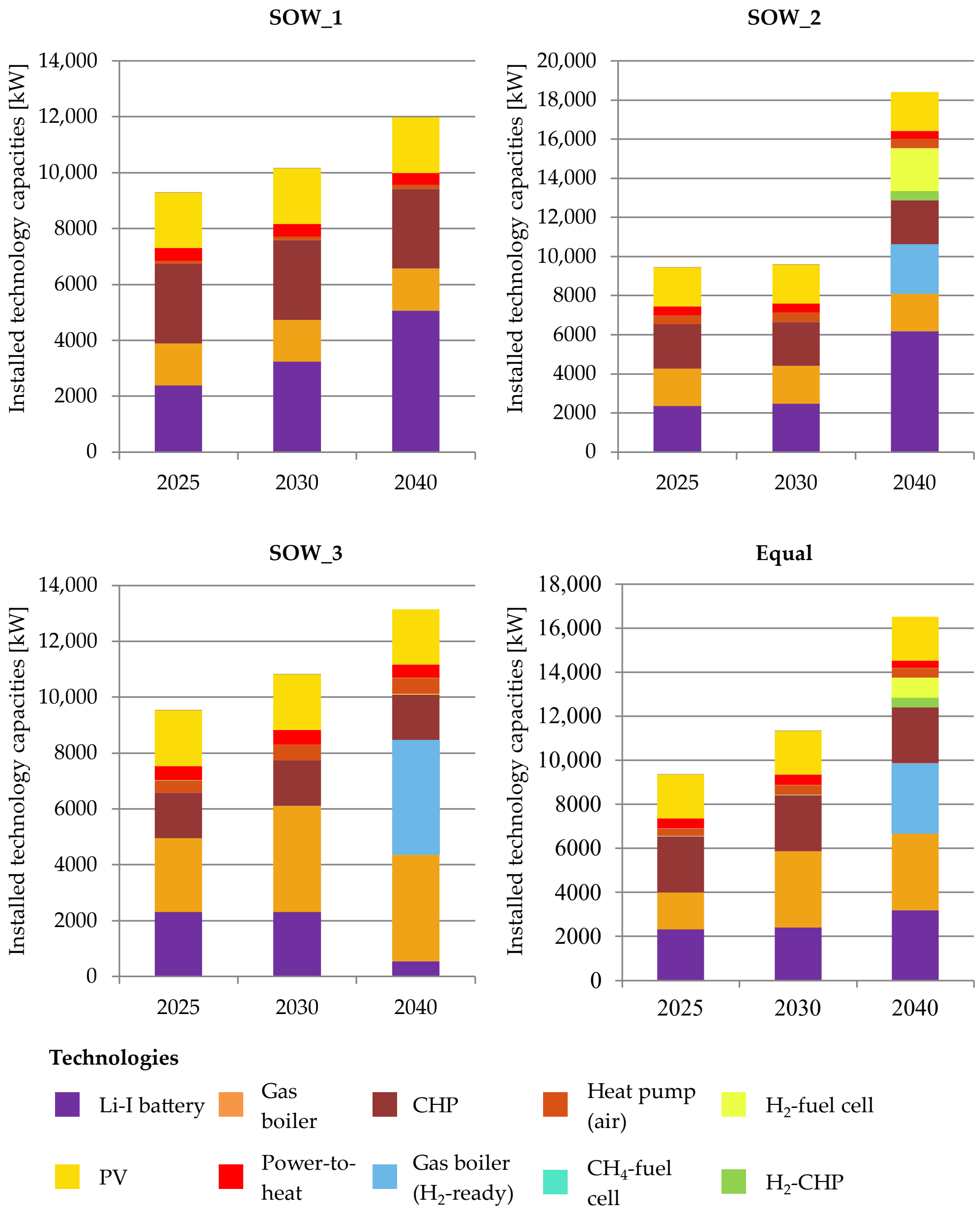


Figure 23. Installed technologies for different scenarios (myopic_years, without CCS).

The significantly higher STCDs of the scenarios, but also the stronger robustness of the SP solutions persists for the scenarios that are optimised by using the method of perfect foresight (see Figure 24). In line with the results of Section 3.1, the STCD of the perfect foresight scenarios is a rough combination of the myopic and myopic_years scenario results. Again, the deviation is less than that of the myopic scenarios, which is due to the previously-installed technologies available to the system, but the pattern of deviation across the scenarios is more in line with the myopic results, as all years are optimised at once.

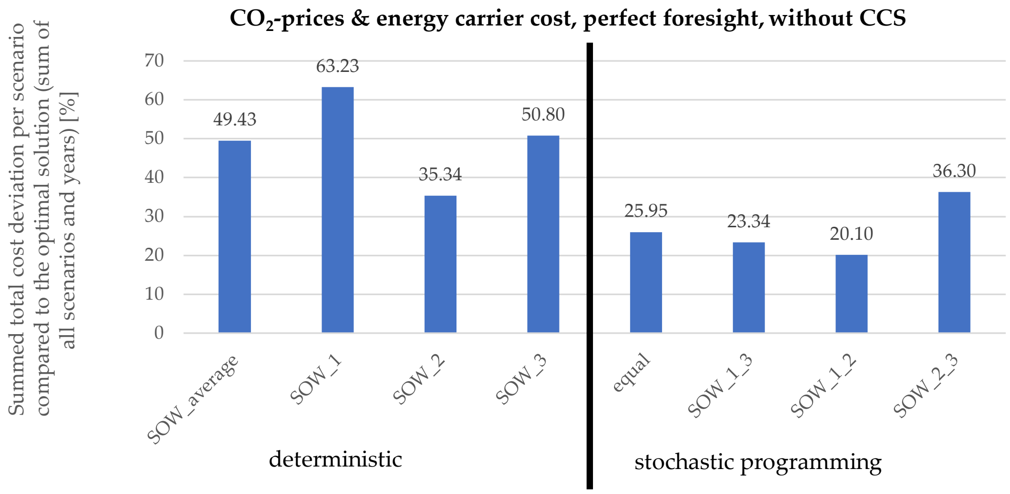


Figure 24. STCD per scenario for uncertain CO_2 prices and energy carrier cost (perfect foresight, without CCS).

Interim Conclusion

First, the results of Section 3.2 underline the value SP can add to the optimisation of energy systems if strong path dependencies occur. In each of the deterministic scenarios, the optimal solution builds around another predominant energy system structure. Due to the very scenario-specific energy systems, the solutions are fragile once the framework conditions change, which manifests in the high STCDs. In contrast to the deterministic method, the SP method generates solutions that differ from the deterministic ones and are considerably more robust against changes in the assumed scenario settings. This is underlined by lower STCDs for all SP scenarios compared to the deterministic solutions.

In comparison to Section 3.1, the STCD level of the results in Section 3.2 is significantly higher for all optimisation approaches. This emphasises that, with a broader uncertainty framework, the path dependencies may be stronger and the optimal energy system configuration differs substantially across the defined scenarios. Organisations that plan to optimise their decarbonised energy systems should consider different uncertainties, and should not limit their analysis to uncertain CO_2 prices.

4. Discussion

The results in Sections 3.1 and 3.2 show the advantage of SP, which generates more robust solutions for both settings. The advantage of this robustness is fully visible for the high scenario in Section 3.1 and all scenarios of Section 3.2, where strong path dependencies occur. The deterministic solutions are fragile in this setting, and the cost increases significantly once the parameter values deviate from the assumed values (see Figures 10, 15, 19 and 20).

The STCDs reduce if technologies that are installed in previous years are considered (Det_myopic_years and Sto_myopic_years). As already mentioned, this setting builds on the assumption that an organisation would maintain technologies even though it does not plan to use them anymore. As already discussed, this assumption is at least questionable (in context of Figure 17). Organisations might decommission technologies that they do not plan to use anymore and do not maintain two technologies to meet the same energy demand (e.g., CHP and boiler). In this context, SP finds a robust solution that can react to all assumed future scenarios by installing different technologies, but explicitly states which technologies are required to achieve a certain level of robustness.

Even though the decision setup of a two-stage SP is more complex than that of deterministic optimisation, the question remains in which use cases the SP setup is (fully) valid. The setup assumes that the investment decision must be made right away and for the whole energy system at once. Often, decision makers decide on one technology at a time and can update the optimisation models once new information is available. However, the problem of path dependencies for long time horizons may remain. In that case, the single strategy of SP might be more beneficial than a variety of different deterministic scenario results, as explained in the introduction. With the single hedging strategy, SP identifies which technologies are the most promising ones and gives an indication on "risk-averse investments" [27]. Especially with extreme scenarios (e.g., autarky targets), SP can be indispensable in order to adequately capture uncertainties [89]. The comparison of the SP and the deterministic solutions allows the identification of technologies that are more common in the SP solutions and might represent "super-hedging" actions [6]. In the context of the results of Section 3.2, this might be the H_2-CHP, which is predominantly installed in the SP solutions.

Nevertheless, SP may fail to deliver robust solutions once the parameters change in a way that is not covered by one of the assumed scenarios (e.g., a disruptive scenario). This might especially apply to disruptive scenarios where path dependencies occur, since the path dependency is not detected by SP. Even though the use of scenarios is a flexible way to deal with uncertainties, defining disruptive scenarios and their probabilities is difficult [90].

Limitations of This Work

The presented optimisation focuses on the fast-developing environment of energy systems and stretches till 2040, which is a long-time horizon. This probably makes the correct prediction of possible future input parameter values impossible and the assumptions are, to a certain degree, arbitrary. Additionally, due to the high interwovenness of the factors, developments in the political and energy economic environment can negate the benefits of previously-made investment decisions [89]. In this context, SP can generate robust solutions that hedge against the defined SOWs. However, not all uncertainties can be considered for the optimisation, which is mainly due to two reasons. First, uncertainty-related information is necessary to actually incorporate the uncertainty into the model [6], and the results of SP are highly dependent on the probability distribution (including its representation in the scenarios) [89]. Second, SP suffers from the curse of dimensionality, which increases the possible SOWs exponentially with increasing numbers of uncertain parameters and decision stages [6,51]. However, considering more uncertainties might lead to path dependencies that the current model setup does not detect. Therefore, this energy system model setup, as with energy system models, should not be perceived as a "physically verifiable model" [26] [26,91] or "fundamental truth" [26], but more as a "source of possible storylines […]" [26] [26,92].

5. Conclusions

The pressure to develop resilient decarbonisation plans is increasing for organisations around the world. For organisations' energy systems, the transformation pathways into a decarbonised future are often planned with energy system optimisation methods (ESOMs). As the energy system environment is very intertwined and changes in certain variables can have rippling effects on other variables and the optimal transformation pathway, the planning involves numerous uncertainties. Even though the input parameters are uncertain, energy optimisation models usually work with the assumption of perfect knowledge of all input parameters (deterministic models). To address the uncertainty in the framework of deterministic models, different methods such as scenario or sensitivity analysis are used. However, these methods have shortcomings and the use of methods that explicitly consider uncertainties is a best practice in the context of ESOMs [6,25]. One method which explicitly addresses the problem of uncertainty in the context of sequential (energy system) optimisation is stochastic programming (SP).

This work assesses the benefits of using two-stage SP in the context of energy system optimisation, with uncertain CO_2 prices and energy carrier cost as two important but uncertain input parameters. Additionally, CO_2 prices are gaining interest as more and more organisations use them in the context of internal carbon pricing. The academic literature has not analysed this aspect so far, and this work closes the knowledge gap with its novel analysis. For a broad investigation, the analysis is split into scenarios with uncertain CO_2 prices and scenarios with both uncertain CO_2 prices and uncertain energy carrier costs.

The results show that:

- As soon as path dependencies occur, the simple two-stage SP yields more robust results than all deterministic methods. The summed total cost deviation (STCD) is, for most SP solutions, only half of that of the deterministic solution in the case of uncertain CO_2 prices and energy carrier costs (myopic, with CCS) and, for the worst scenario (medium-high), is still 4% better than the most robust deterministic solution;
- For the scenarios where no strong path dependencies occur (uncertain CO_2 prices, myopic, without CCS), the STCDs of the deterministic and SP solutions do not differ that much, and SP has only around 2% lower STCDs;
- Independent of the optimisation approach, the STCD is lower for those scenarios where previously-installed technologies are considered, but the pattern within the results persists (more robust SP solutions). Furthermore, it is debateable how applicable the assumption of the availability of previously-installed technologies is to a real-world decision situation, as discussed in Section 4;
- SP provides a robust hedging strategy and names exactly which technologies are necessary to achieve the robustness. This may help decision makers, as it avoids leaving them in the previously-described dilemma of deterministic solutions with a variety of different scenario results;
- Organisations should consider a variety of different uncertainties in the context of optimising their energy systems, since a higher number of uncertain parameters might lead to different path dependencies;
- A CO_2 price-focused analysis of transformation pathways for energy systems might be too narrow. Consequently, (internal) carbon prices should be analysed in the broader energy system context to find important path dependencies that should be considered during the design process. For the analysed case study, this results in the full exploitation of all available renewable potentials (PV) and the installation of hydrogen-ready technologies, which allow a fuel switch once the relevant parameters change.

Based on this work, different directions of future research can be pursued further. First, knowledge of how to reduce the computational demands of SP should be broadened. Only by reducing these demands can SP be used in increasingly complex optimisation settings. Second, SP should be tested on other variables and scenario settings to further investigate where strong path dependencies occur, and to prove the advantage of SP in these contexts. Third, SP should be benchmarked against other methods that consider uncertainty. With this comparison, knowledge of the different methods increases and situations may be identified where certain uncertainty-considering methods are more suitable than others.

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Nomenclature

A	Coefficients of the constraints
b	Right-hand side of first stage constraints
CAPEX	Capital expenditure
CHP	Combined heat and power
CO_2	Carbon dioxide
c^T	Cost coefficients
ξ_k	(q_k, T_k, W_k, h_k) parameters for the second stage problem of scenario k
ESOMs	Energy system optimisation models
$g(x)$	Objective function
GAMS	General Algebraic Modelling System
GHG	Greenhouse gas
h	Right-hand side of the second stage constraints
H_2	Hydrogen
$k \in \mathbb{N}^K$	Possible future states of the world (K must be a finite number)
kW_P	Kilowatt peak
LT DAC CCS	Low temperature direct air capture carbon capture and storage
MILP	Mixed-integer linear programming
OPEX	Operational expenditure
PV	Photovoltaic
p_k	Occurrence probability for scenario k
$Q(x, \xi_k)$	Optimal solution of the second-stage problem
$q^T y$	Cost for the recourse action, which is done after the uncertainty resolved (corrective action)
SOW	State of the world
SOWs	States of the world
SP	Stochastic programming
STCD	Summed total cost deviation
T	Transition matrix for the first-stage variables
W	Recourse matrix (cost of recourse)
X	Set, defined by a finite number of constraints
$x \in \mathbb{R}^n$	First-stage decision vector
$y \in \mathbb{R}^m$	Second-stage decision vector
y_k	Second stage decision vector for every scenario ξ_k
$z \in \mathbb{N}^Z$	Defined time horizon

Appendix A

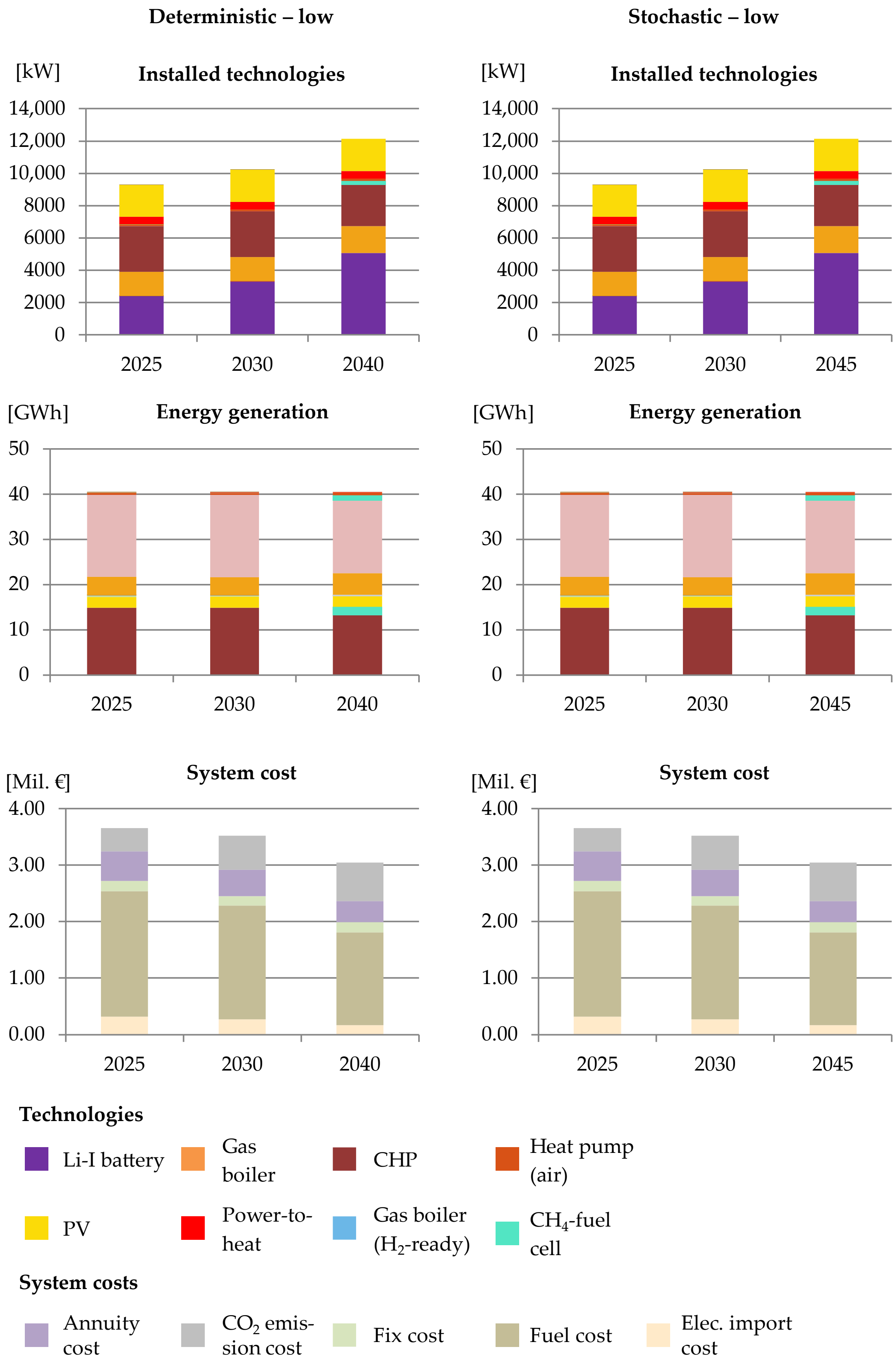

Figure A1. Scenario results for the deterministic–low and stochastic–low setting. Proves the correct implementation of stochastic programming into DISTRICT.

Appendix B

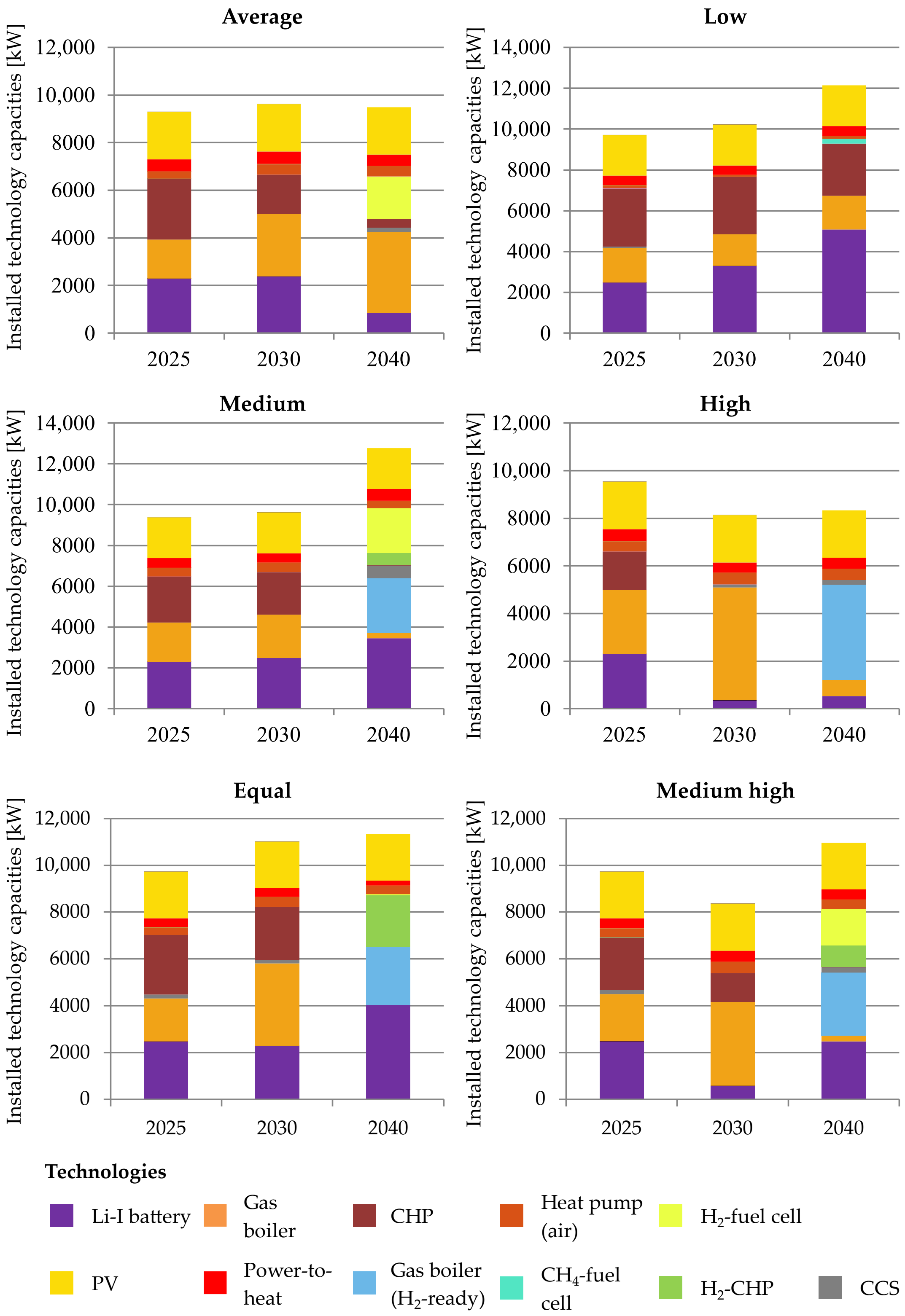

Figure A2. Installed technologies for different myopic scenarios with uncertain CO_2 prices and energy carrier costs (myopic, with CCS).

Appendix C

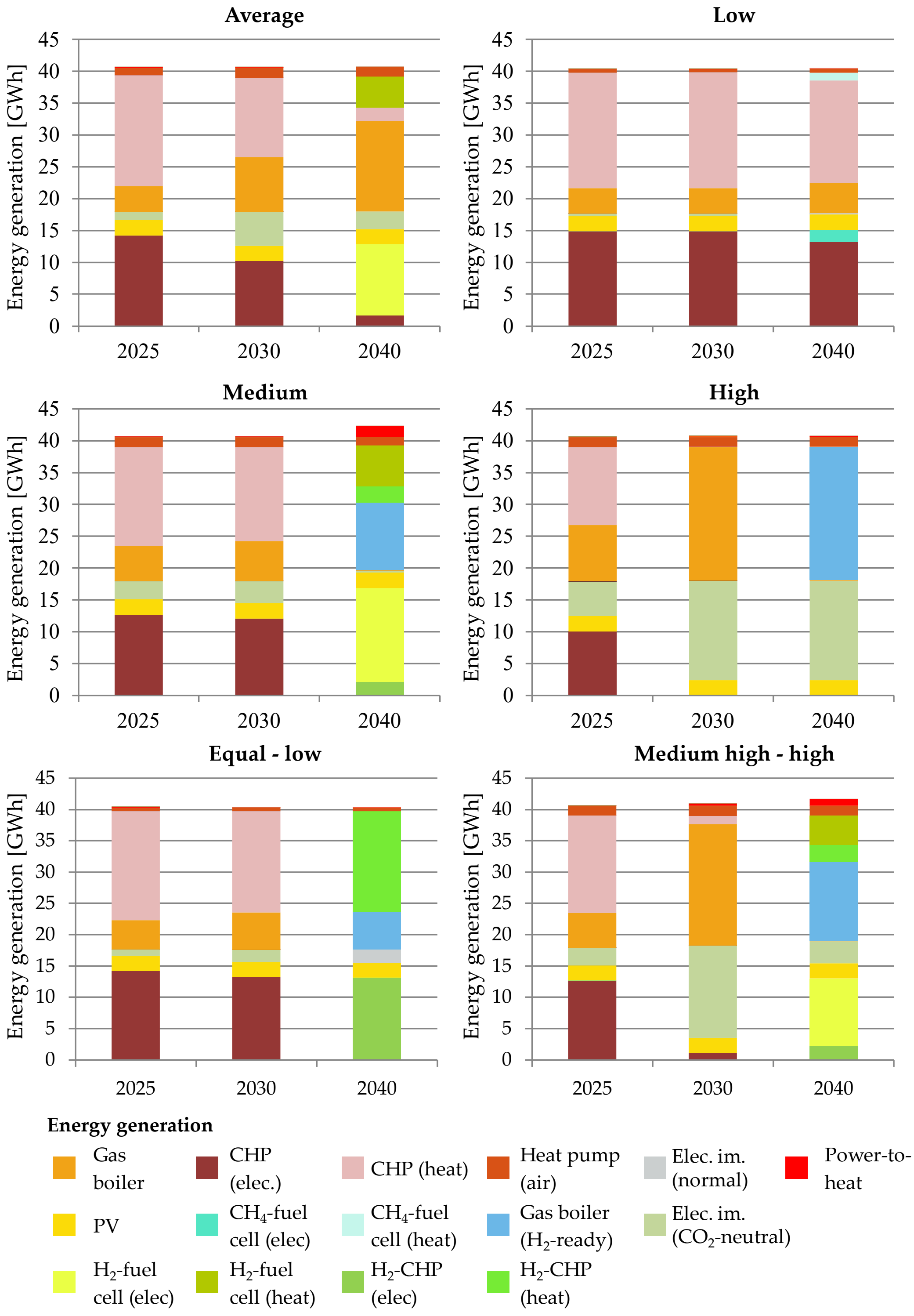

Figure A3. Energy generation for different scenarios with uncertain CO_2 prices and energy carrier costs (myopic, with CCS).

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