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Transitioning remote Arctic settlements to renewable energy systems – A modelling study of Longyearbyen, Svalbard

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HIGHLIGHTS

- We present a new stochastic long-term energy model for a remote Arctic settlement.
- We show the importance of a proper representation of solar and wind variability.
- An energy system based on renewables is found feasible, reliable and affordable.
- Energy efficiency plays an important role in a transition to a low carbon settlement.
- Allowing some CO_2 emissions reduces costs and improves energy security.

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ABSTRACT

As transitioning away from fossil fuels to renewable energy sources comes on the agenda for a range of energy systems, energy modelling tools can provide useful insights. If large parts of the energy system turns out to be based on variable renewables, an accurate representation of their short-term variability in such models is crucial. In this paper, we have developed a stochastic long-term energy model and applied it to an isolated Arctic settlement as a challenging and realistic test case. Our findings suggest that the stochastic modelling approach is critical in particular for studies of remote Arctic energy systems. Furthermore, the results from a case study of the Norwegian settlement of Longyearbyen, suggest that transitioning to a system based on renewable energy sources is feasible. We recommend that a solution based mainly on renewable power generation, but also including energy storage, import of hydrogen and adequate back-up capacity is taken into consideration when planning the future of remote Arctic settlements.

1. Introduction

Remote Arctic energy systems are usually characterised by a dependence on imported fossil fuels [1,2]. Concerns about volatile fuel costs, energy security, and climate change give rise to many remote Arctic communities looking towards renewable energy sources as potential solutions. Rapid cost-reductions and technological development have led to renewables becoming an increasingly attractive option. Particularly solar and wind are emerging as mature and cost-competitive technologies, even for energy systems in remote Arctic locations.

The transition to future energy systems is often aided by the use of energy modelling tools. Several tools exist, with various capabilities, features and applications ranging from analysis of detailed power systems to the global energy system (see reviews by Connolly et al. [3], Ringkjøb et al. [4], Hall & Buckley [5] and Foley et al. [6]). Many previous modelling studies have looked at remote isolated communities, but there are only a few focusing on Arctic locations [7,8]. For example, the HOMER (Hybrid Optimization of Multiple Energy Resources) modelling tool [9] was applied to study the electricity system serving the small settlement at the island of Grimsey located north of Iceland (66.5°N) [1]. They analysed three scenarios for delivering electricity, respectively a diesel-wind, diesel-wind-hydrogen and a wind-hydrogen scenario. Their results showed that a system consisting of wind, hydrogen and diesel was recommended, achieving a renewable energy fraction of 92% and a payback period of less than four years. Furthermore, the TIMES (The Integrated MARKAL-EFOM System) modelling framework [10] was used to study the energy system at the Faroe Islands (62°N) [11], highlighting the importance of electrification of heating and concluding that renewable energy technologies will be competitive with fossil fuels in a very short time, even in the Arctic. Streymoy, the largest island on the

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Faroe Islands, was also one of six islands investigated in a study using a MATLAB/Simulink model to determine cost-optimal system configurations [12].

A larger literature has addressed remote and isolated locations at lower latitudes, such as the island of Pulau Ubin north-east of Singapore [13], the island of Dia in the Cretan Sea [14] and other locations in the Mediterranean [15] Even though the climatic conditions in such locations are vastly different from the Arctic, several similarities make these studies relevant also in an Arctic context. Many of these locations are also dependent on imported fossil fuels, have a need of improving energy security and a large distance to highly populated areas. They are therefore evaluating renewables as alternatives [8].

Wind and pumped hydro storage (PHS) was for example evaluated for increasing the share of renewables and aid in desalination of water on the S.Vicente Island in Cape Verde in a study using the modelling tool H_2RES [16]. Furthermore, a 100% renewable electricity supply for Reunion Island was modelled in TIMES [17], with large amounts of solar, biomass, and important contributions from storage and demand response. TRNSYS [18] was used in combination with HYDROGEMS [19] in a modelling study of the former wind/hydrogen demonstration project at Utsira in Norway [20]. The goal of this demonstration project was to demonstrate how hybrid renewable energy and hydrogen systems could provide electricity to communities in remote areas. The authors concluded that the project successfully demonstrated the potential of wind/hydrogen systems to supply remote locations, but that technical improvements and cost reductions were needed to be competitive with existing solutions.

In this study, we use the TIMES modelling framework to develop and apply a new stochastic model for isolated Arctic settlements. The model takes into account the variability of short-term solar and wind generation as well as the uncertainty in electricity and heat loads. A common approach, also when modelling larger energy systems, is to treat solar and wind generation as deterministic inputs. This has previously been shown to potentially overestimate the contribution from variable renewable energy sources and lead to suboptimal investments [21–23]. Long term persistence is characteristic for geophysical time series including solar and wind resources [24]. In a harsh Arctic climate, where security of energy supply is crucial for the inhabitants, taking into account the possibility of periods with low solar and wind resources is highly important.

Stochastic modelling of short-term variability in TIMES is a relatively new technique, first applied in a study of the Danish energy sector [22], but which to the authors' knowledge has never been applied to local isolated energy systems. Our hypothesis is that a stochastic approach is even more important in a small isolated energy system than in a large national or international system. As has been pointed out by Connolly et al. [3], TIMES models have mainly been applied to study energy systems on larger scales up to the global energy system, and are not commonly used to assess remote and isolated communities. However, we believe that the stochastic approach enables the use of TIMES-based long-term energy models to study small isolated energy systems, thus widening the range of possible applications of the TIMES modelling tool.

The importance of a stochastic approach is investigated through a case study focusing on the Norwegian high-Arctic settlement of Longyearbyen (78.2°N). Presently, the settlement covers its needs for electricity and heat from Norway's only coal-fired power plant supplied by locally mined coal. With a declining coal industry, an old energy infrastructure, and the use of greenhouse-gas-emitting coal as the main source of energy, there is a need of planning for securing the future energy supply. This makes this study highly relevant to decision-making, and well suited for investigating the importance of a stochastic modelling approach for remote communities in general.

The objective of the present study is to develop a dynamic model to analyse and optimise an affordable and reliable future supply of electricity and heat primarily based on renewable energy sources and test it on a realistic case where necessary data are available. The model selects which energy system components to invest in over time based on bottom-up cost estimates for available components, minimizing total discounted investment and operational costs over the time period. The study demonstrates the importance of a realistic representation of solar and wind variability in long-term energy models, through the application of a stochastic modelling approach.

2. The Longyearbyen case-study

Longyearbyen was founded in 1905 for coal mining purposes, and is located on the Svalbard archipelago barely a thousand kilometres from the North Pole (see Fig. 1). Now, the more than century long coal mining era is coming to an end. Years of low coal prices have led to economic difficulties for the state-owned mining company "Store Norske Spitsbergen Kulkompani». In autumn 2017, the Norwegian government decided a permanent closure of the mines Svea and Lunckefjell [25]. This leaves the smaller mine number 7 as the only Norwegian coalmine to be kept in operation on Svalbard, and its main purpose is to supply the power plant in Longyearbyen. The coal reserves in mine 7 are expected to be able to supply the power plant for 10 more years, after which coal has to be imported if a new energy system is not in place.

Since Longyearbyen houses the only coal-fired power plant in Norway, there is particular political focus on reducing emissions from Longyearbyen. The power plant is the main component of the current energy system in the settlement, providing about 40 GWh electricity and 70 GWh heat to the about 2100 year-round residents and 150 000 person-days of visitors, mostly in summer [26,27]. Most of the electricity is consumed in the industrial sector, whereas households and the service sector consume the majority of heat [28]. The power plant was built in 1982 and faces challenges regarding ageing equipment, though recent and comprehensive upgrades have extended the potential lifetime of the plant for about another 20 years [27].

In addition to the coal-fired power plant, there are five diesel generators to cover peak electricity demand and to serve as reserve generation capacity. There is also a reserve heat-exchanger that can be fed directly with steam from the two coal-fired boilers in case of failure on the back-pressure turbine. Six oil-fired boilers are also placed around in the district heat network for reserve and to cover peak heat demand. There is also a small amount of solar PV installed in the settlement, about 57 kW on the airport and about 28 kW on residential buildings in Longyearbyen [29]. In total, the energy supply in Longyearbyen emits about 60 000 tons CO_2 annually [11].

Against this background, there is a need of planning the future energy supply of Longyearbyen. The Norwegian Ministry of Petroleum and Energy has already started investigating different options, and will decide the future of Longyearbyen's energy system in the near future [30]. The Norwegian Government stresses that the future energy supply in Longyearbyen should be sustainable and cost-effective, as well as provide adequate security of supply.

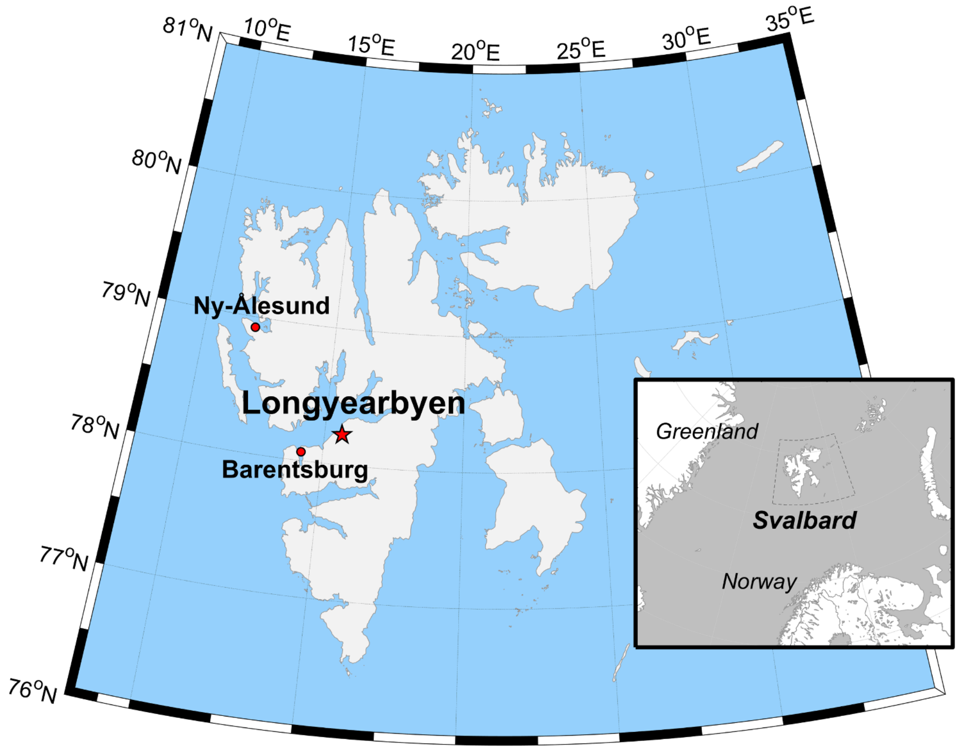

Fig. 1. Map of Svalbard and its surroundings.

3. Modelling methodology

3.1. TIMES-Longyearbyen

TIMES (The Integrated MARKAL-EFOM System) is a modelling framework widely used to develop models of local, national, international or global energy systems [10]. It follows a bottom-up approach, and performs long-term analyses of the entire or parts of the energy system. The TIMES modelling framework uses linear programming to minimise the total system cost, through optimal decision making on infrastructure investments, systems operation and imports of energy carriers. An extensive documentation detailing the TIMES modelling framework can be found in [10].

Based on the TIMES modelling framework, we have developed and applied the stochastic long-term energy model TIMES-Longyearbyen in this study. TIMES-Longyearbyen consists of the single isolated region of Longyearbyen. The base-year is 2015, and the base case global discount rate has been set to 4% in compliance with recommendations from the Norwegian Ministry of Finance in long-term socioeconomic studies [31]. We also assess the sensitivity of the model results on the discount rate in Section 4.6. The currency chosen is Norwegian kroner (NOK), and all costs, prices etc. are given in 2015-NOK.

The model horizon is from 2015 to 2050, and investments are made every 5th year (Fig. 2). In order to represent the operation of the system, e.g. through demand profiles and variable renewables, we use a high temporal resolution within each period (Fig. 2). Each year is represented by 192 time-slices, distributed over 24 h over two days (one weekday and one weekend day) per season; spring (March, April and May), summer (June, July and August), autumn (September, October, and November) and winter (December, January and February).

Load profiles for electricity and heat have been derived from two real datasets of heat and energy generation from the power plant in Longyearbyen (Longyear Energiverk), given on an hourly basis for 2017 and 2018 [32]. The datasets were used to calculate representative daily load profiles, and as input for the stochastic modelling.

For each of these representative time-slices, the demand of heat and electricity must be covered by the set of technologies in the model. For the present study, in addition to the current system in Longyearbyen,

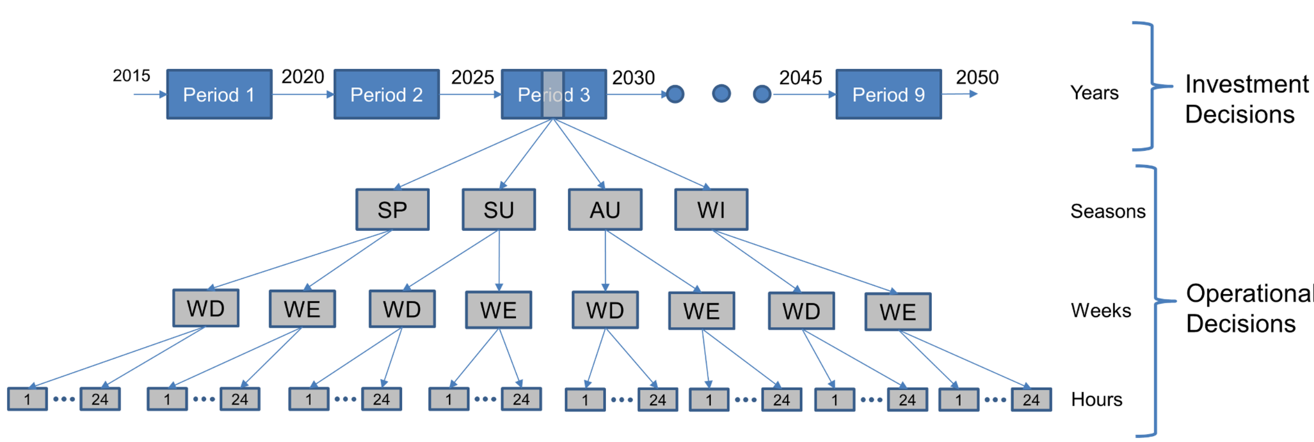

Fig. 2. Time-slice division in TIMES-Longyearbyen.

we have included a broad set of technologies available for future investments (solar photovoltaics, solar thermal, onshore- and offshore wind, hydrogen electrolysers, hydrogen storage, hydrogen fuel-cells, lithium-ion batteries, geothermal and seawater-based heat pumps, electric boilers, underground thermal energy storage, diesel generators, gas turbines, gas cogeneration plants and energy efficiency measures). Costs of these technologies are as far as possible based on recent data from the Norwegian Water Resources and Energy Directorate with the aim to use costs that are both relevant in a Norwegian context and state of the art in a quickly changing energy sector [33,34]. The present and future costs of these technologies, as well as their technological parameters (efficiency, technical lifetime etc.), are summarised and referenced in Table S1 in the supplementary materials.

Several technologies were omitted from the study due to qualitative considerations, e.g. hydropower and biomass due to lack of potential. Another example is electricity generation through an Organic Rankine Cycle (ORC) using a low temperature geothermal heat source. Preliminary test drillings have shown promising conditions for geothermal energy in and around the settlement, with ground temperatures significantly higher than experienced in mainland Norway [35]. With its independence of weather conditions, year-round availability and its ability of serving as a base-load generator, geothermal electricity may become a useful component of the energy system in Longyearbyen. However, due to the high uncertainty, both in terms of the actual resource potential and in terms of costs, geothermal electricity was not assessed in this study.

Solar PV panels with single-axis tracking has a slightly higher performance than fixed panels, but are omitted from the study due to higher costs and the reduced durability associated with moving parts in harsh arctic conditions with both snow and ice.

Another potential technology not modelled in this study, is carbon capture and storage (CCS). Studies concerning the potential of CCS for Longyearbyen have been undertaken at the University Centre in Svalbard (UNIS) [36]. CCS could be an option to extend the operation of the coal-fired power plant or used with new gas based generators. We have not included CCS due to uncertainties about storage integrity, costs and maturity of related technologies.

3.2. Projection of end-use energy demand

Projections of future end-use energy demand are supplied exogenously to TIMES-Longyearbyen, and are important drivers for modelling results. Since Longyearbyen is highly influenced by policy, this is a challenging task.

Fig. 3 shows the historic evolution of heat- and electricity demand in Longyearbyen from 2000 until 2015. A sharp population increase from about 1500 to about 2100 residents between 2000 and 2010 was a strong driver for increased heating needs in the settlement [37]. In the period between 2010 and 2015, the population was quite stable and lead to the heat demand stabilizing around 70 GWh (see Fig. 3). On the other hand, the generation of electricity has been relatively constant

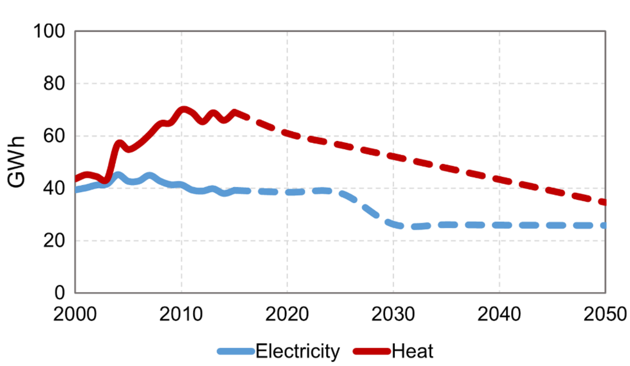

Fig. 3. End use demand projection.

through the whole period, which can be explained by a gradual shift from electricity demanding mining activities to less demanding activities such as tourism, culture and education. In our calculations of future end use energy demand, we have assumed that the population is kept stable at the current level.

The energy demand is split into three main sectors; households, services and industry, where all three sectors require electricity and heat as an energy service. We follow the methodology presented in [38], where the development in end-use energy demand is calculated as the product of an activity (e.g. m^2) and an energy indicator (e.g. kWh/m^2y).

There is a large potential for increased energy efficiency in Longyearbyen, particularly for heating. Firstly, the historic and present cost-structure where the residents only pay for heating per square meters and not for actual energy use, gives no incentives to reduce energy consumption. Secondly, more than 50% of the building stock in Longyearbyen was built before 1970 and is not very energy efficient [28]. New buildings must adhere to current building regulations (Norwegian standard TEK17), and we thus assume that new and renovated buildings will cut their specific heat usage from about 500 kWh/m^2y to 150 kWh/m^2y [39]. Due to the assumption of a constant population towards 2050, the total building area stays the same but is replaced by new and renovated buildings at a rate of 2.3% per year [40]. In addition, we assume that energy efficiency in the service sector increases by 1% per year due to the new building regulations [38]. The development of electricity use in the household and service sector is based on development in electricity use per capita in mainland Norway [40]. In the industry sector, the mining activities and the coal-fired power plant itself constitutes 30% of the electricity use in the settlement. Since we assume that in 2030 both the coal-fired power plant is decommissioned and the mining activities are stopped, this leads to a reduction in electricity consumption of 12 GWh, visible as a significant drop in Fig. 3. With these assumptions, the demand for electricity and heat is projected to decrease by 13 GWh and 34 GWh respectively by 2050 (34% and 50%).

Additional energy efficiency improvement may be achieved as a result of the model optimisation. It allows investments in energy efficient equipment including heat pumps, solar thermal collectors and four other energy efficiency measures; energy monitoring, insulation and tightening, technical equipment and energy management (Table S2 in the supplementary material) [38,41].

Since the development in the settlement is highly dependent on political considerations, our energy demand projection represents only one of several possible scenarios for the future of Longyearbyen. We have therefore assessed the sensitivity of the modelling results to the demand projection by testing alternative demand projections (discussed in Section 4.6).

3.3. Solar and wind resources

In this study, we apply hourly solar and wind electricity generation estimates based on renewables.ninja, a web application based on the GSEE model (Global Solar Energy Estimator) [42] and the VWF model (Virtual Wind Farm) [43]. The models use meteorological data from the MERRA reanalysis [44], as well as user-specified data such as the location, hub-height, wind turbine model, orientation and tilt (Tables 1 and 2) as input to produce hourly datasets of solar and wind generation.

Five datasets spanning from 01.01.2000 until 31.12.2018 have been retrieved, representing three possible locations for solar PV and two for wind power in and around Longyearbyen. The specifications of the solar and wind farms and their average capacity factors (the ratio of actual energy generation during a given period to the potential generation if producing at nominal capacity during the same period) are shown in Tables 1 and 2.

The datasets for solar PV generation have been used directly, and their capacity factors are comparable to realised capacity factors on

Table 1
Wind generation data.

Type	Location	Hub height (m)	Turbine size (MW)	Capacity Factor (%)
Onshore	78.2°N, 15.4°E (Platåfjellet)	90	5	26.3
Offshore	78.4°N, 14.7°E (Isfjorden)	119	10	31.9

Table 2
Solar generation data.

Type	Location	Orientation (Azimuth)	Tilt	Avg. Capacity Factor (%)
Ground	78.2°N, 15.4°E (Platåfjellet)	180° (south)	30°[1]	7.67
Rooftop	78.2°N, 15.8°E (Longyearbyen)	315° (northwest)	20°	6.03
Rooftop	78.2°N, 15.8°E (Longyearbyen)	135° (southeast)	20°	7.22

[1] Optimal tilt obtained from the software PVSyst by Thorud [45]. There is no sun during the polar night (March to October), which leads to a low optimal tilt angle close to summer conditions.

already installed residential solar panels in Longyearbyen. Existing solar panels, which were installed in 2013, have exceeded expectations with an annual capacity factor of 7.1% [29]. In TIMES-Longyearbyen, we limit the amount of residential solar installations by estimations of available roof area based on [45].

For wind power, renewables.ninja offers a series of power curves for various wind turbines, but to be able to model newer and bigger turbines, we have used raw wind speed data retrieved from renewables.ninja in combination with power curves of a 5 MW [46] and a 10 MW [47] wind turbine for onshore and offshore applications respectively (Renewables.ninja has recently been updated with additional wind power curves). As a quality control, the MERRA-based wind speed data has been compared to observations from the Norwegian Meteorological Institute from the relevant location Platåberget close to Longyearbyen in the period 03.02.2018 to 31.12.2018 [48], achieving a good fit with the MERRA reanalysis data (correlation coefficient of 0.76).

Fig. 4, which shows the hourly capacity factor for solar and wind through one climatological year (averaged over the 19-year period), indicates that solar and wind could complement each other well in Longyearbyen. The solar resource is strong during the summer months, but not present during the polar night from October until March. Inversely, the wind resource is at its strongest during winter from September to April, but weaker during summer.

3.4. Stochastic modelling approach

Stochastic modelling in TIMES involves taking into account the uncertainty of various input parameters to the system optimisation [49]. This contrasts deterministic model versions, in which the decision-making assumes that all input parameters are certain.

In TIMES-Longyearbyen, we model the short-term uncertainty of seven stochastic parameters, corresponding to electricity generation from solar PV (three possible locations), wind power (onshore and offshore), and the demand of electricity and heat. For this application, it is particularity important to capture the intermittency of solar and wind to ensure energy system robustness. As already mentioned, the solar PV and wind power data are based on Renewables.ninja [42,43], whereas the electricity and heat data are based on real measurements from the power plant in Longyearbyen [32].

A two-stage stochastic model is applied [50,51], and is illustrated by its scenario tree in Fig. 5. Here, the first stage involves investment decisions made over the whole modelling horizon based on the expected outcome of the operational scenarios but without knowing their true realisations. This is a key property of the approach, as the investments are not only optimised for one set of load profiles and renewable generation profiles, but take into account a wide range of possible outcomes. This leads to a set of investments that are feasible and identical for all sixty operational scenarios, important for e.g. security of supply. The true outcome of the operational scenarios is first revealed in the second stage, where operational decisions are made across all scenarios and periods. Each branch in the second stage corresponds to

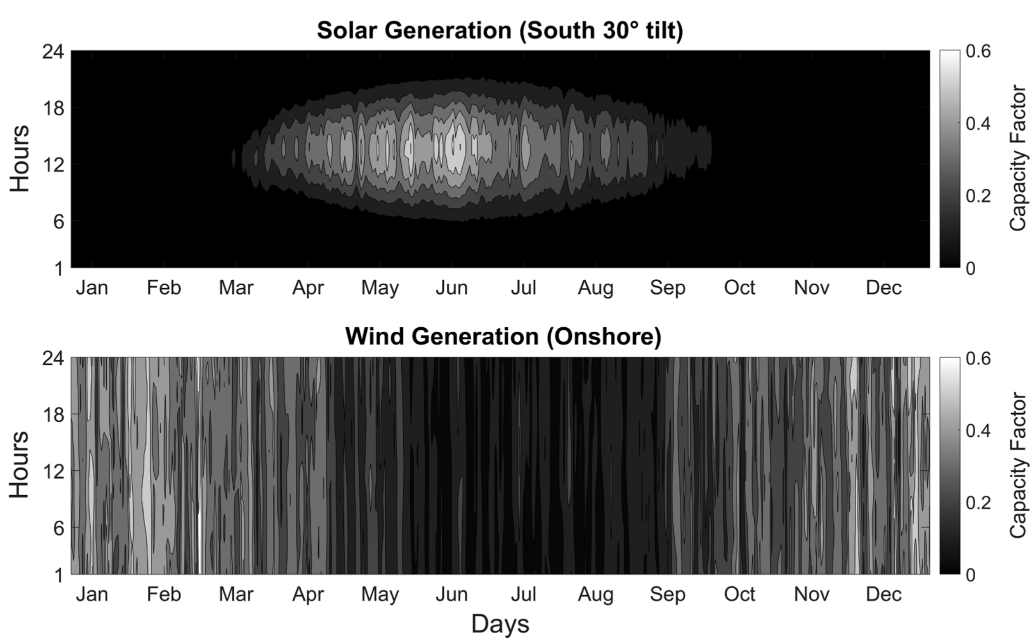

Fig. 4. Solar and wind resources.

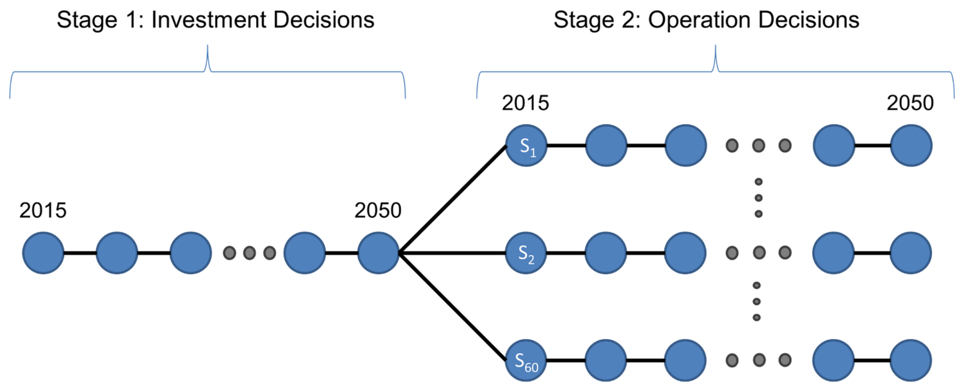

Fig. 5. Illustration of a two-stage scenario tree with sixty operational scenarios (adapted from [53]).

one operational scenario, corresponding to different realisations of the stochastic parameters, all with the same probability of occurrence. We employ a multi-horizon structure [51], in which investment and operational decisions are made simultaneously, and which assumes no dependency of operational decisions between model periods. This means there is no learning effect from observing operational scenarios, which significantly reduces model size, and is also a good approximation of real decision processes since including such learning effects would be similar to assuming perfect foresight of operational outcomes over the modelling horizon [52].

In TIMES-Longyearbyen, we use sixty operational scenarios to describe our stochastic parameters. Increasing the number of scenarios can improve the robustness of the results, but leads to increased computational effort [54]. The sixty scenarios play an important role in the stochastic modelling approach, as they should reflect the variability of the parameters and in addition represent realistic operational situations. The scenarios are selected from historic datasets through a method that combines two techniques called random sampling and moment matching, based on [22]. This involves:

(1) Random sampling of historical days to construct 60 independent scenarios, where each scenario follows the temporal structure of the model and consists of two sampled days with hourly resolution per season (192 time-slices). The approach gives consistent daily correlations by sampling consecutive hourly values throughout the day, and correlations between the seven uncertain parameters by sampling concurrent days. We sample the days separately for each of the four seasons, assuming no seasonal dependency, and repeat the procedure for each investment period thus also capturing inter-annual variability. A set of scenarios consists of 60 independent scenarios * 24 h * 2 days * 4 seasons * 9 periods * 7 stochastic parameters = 725 760 values.
(2) Repeating this procedure to generate a large amount of possible scenario sets, in this case 10 000 sets.
(3) Calculating the first four moments (mean, variance, skewness and kurtosis) for the historic data and for each of the 10 000 scenario sets.
(4) Finding the deviation of the first four moments of each scenario set to the historical datasets, and select the set of scenarios with the lowest deviation and thus the best fit with the statistical properties of the original datasets.

Fig. S9 in the supplementary materials presents a comparison of the mean, variance, skewness and kurtosis profiles of the selected stochastic scenarios and the historical datasets. The figures show that by following the scenario generation method we achieve a reasonable approximation to the historic data. Furthermore, Fig. S10 in the Supplementary Materials compares the probability density functions of onshore wind and solar PV generation, showing that our model captures their intermittent power generation sufficiently well.

Fig. 6 below illustrates the difference between a deterministic and a stochastic modelling approach. The deterministic profiles are based on the expected value of each parameter, while the sixty stochastic scenarios are selected by the scenario generation method explained in the previous paragraphs. The figure shows a day of solar generation during summer, as well as onshore wind, electricity demand and heat demand during a winter weekday. These days are chosen since generation and consumption are highest during these respective seasons and days. Fig. 6 clearly shows the extra variability modelled in a stochastic approach, with periods of both low and high generation from variable renewables and periods of varying heat and electricity demand. The ability of the energy system to support these realistic operational situations is important for security of supply in the settlement.

3.5. Model cases

We investigate four model cases, each distinguished either by their modelling approach or by constraints that allow us to study specific cases for Longyearbyen's future energy system. All input parameters, such as future technology costs, efficiencies, fuel costs and so on are equal in all model cases. We also assume, in all cases, that the existing coal-fired power plant is decommissioned within ten years from now, so that by 2030 an entirely new energy system will be in place in Longyearbyen. The four model cases are summarised in Table 3 below.

The first model case, *DET*, is a deterministic model version constrained to use only renewable energy sources, either locally available or through imported hydrogen produced elsewhere, presumably in mainland Norway and shipped to Longyearbyen. Its main purpose is to illustrate the difference between a deterministic and a stochastic model version, and to assess and compare the different investment strategies in the two approaches. The DET case is not considered a realistic optimisation of Longyearbyen's future.

The second case, *ISO*, is a stochastic model that constrains all import processes to the island, resulting in a completely isolated energy system that has to draw all its power and heat from locally available renewable energy resources.

The third case, *HYD*, is a stochastic model that allows importing hydrogen from mainland Norway. We also assume that the hydrogen is produced by electrolysis using surplus Norwegian hydro- or wind power rather than steam reformation of natural gas, and thus considered 100% renewable. The cost of importing hydrogen has been set to 35 NOK/kg H_2 [55]. Due to the uncertainty surrounding this future price, the sensitivity of the model results to the hydrogen price has been assessed.

The fourth case, *FOS*, is a stochastic model that permits import of fossil fuels (diesel and/or natural gas) in addition to hydrogen. This has the potential to reduce the storage requirements, help stabilise the grid and reduce the total cost of the system. In addition, if only or primarily used as back-up generation, it would lead to limited amounts of

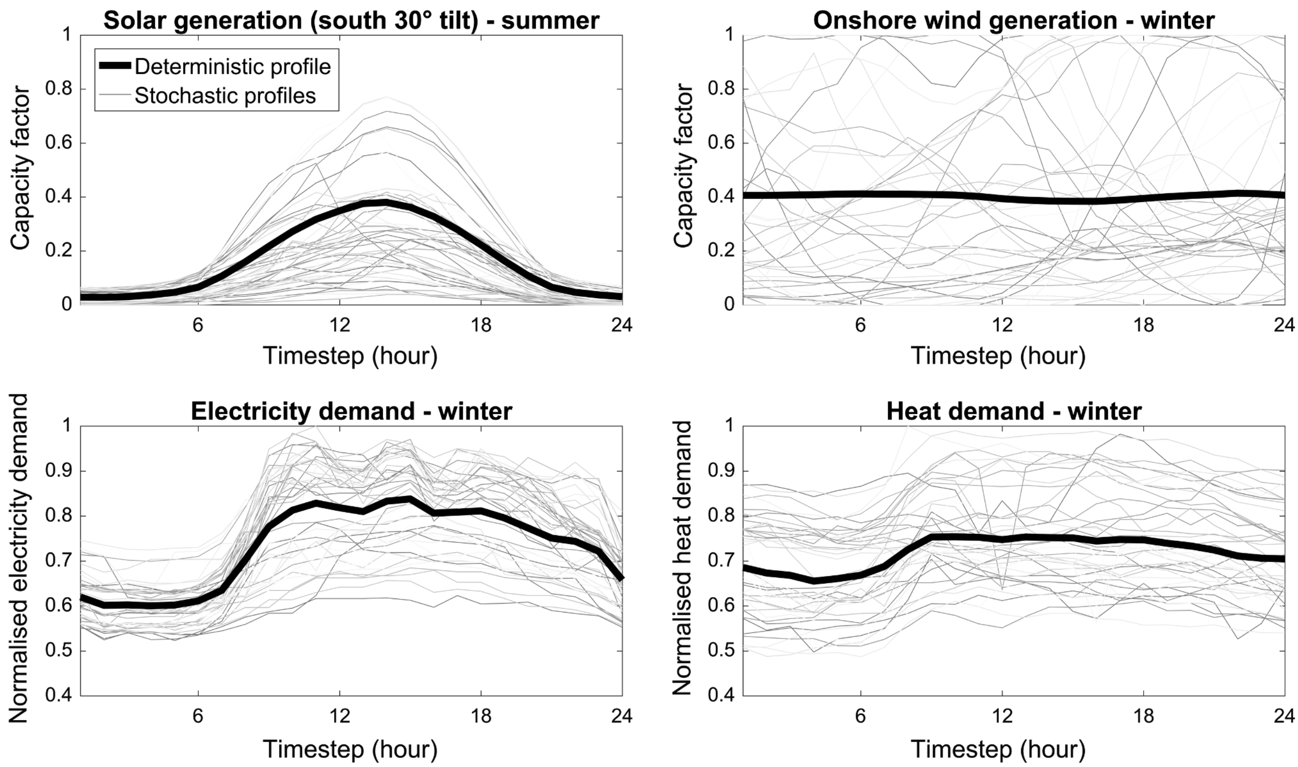

Fig. 6. Deterministic and stochastic daily profiles of hourly capacity factors for solar generation during summer, as well as onshore wind generation, electricity demand, and heat demand during a winter weekday. The thick bold line refers to the daily profile used in a conventional deterministic model, whereas the thin lines in grey are the sixty stochastic profiles selected by the scenario generation method.

Table 3
Model Cases investigated in the study.

Model Cases	Method	Description
DET	Det.	Unrealistic case, included in order to compare model techniques
ISO	Stoch.	Isolated system
HYD	Stoch.	Allowing imports of renewable hydrogen from mainland Norway
FOS	Stoch.	No constraints, i.e. allowing also imports of fossil fuels

greenhouse gas emissions. In the final analysis, we run several additional cases each with a pre-determined maximum level of CO_2 emissions in Longyearbyen exploring options ranging from *HYD* to *FOS*.

4. Results and discussion

4.1. Deterministic (DET) versus stochastic modelling approach

A conventional deterministic modelling approach, which considers only one operational scenario in its optimisation, can give valuable insights, but in this particular case study it could lead to misleading results.

The *DET* model case gives investments in a system heavily reliant on wind power, supplemented by solar power and batteries to smoothen intraday variability (Fig. 10). Heating is largely electrified, and is generated through electric boilers as well as geothermal and seawater based heat pumps. The electrification requires additional electricity, which also plays a part in increasing the required installed electricity generation capacity. In addition, the model decides to invest in energy monitoring, the cheapest alternative of the modelled energy efficiency measures.

As illustrated in Fig. 6, the solar and wind resources in the *DET* model case are based on their climatological features and give an inaccurate description of their true variability. This consequently leads to an overestimation of the contribution of wind power in the model, with wind unrealistically treated as a base-load generator. The case clearly demonstrates that using a deterministic modelling approach could lead to misleading results when variable renewables become a major fraction of installed capacity.

The lack of realism in the *DET* model case is further evidenced by testing the value of stochastic solution (VSS), a test that aims to evaluate the advantage of using a stochastic model version versus a deterministic one [22,56]. It works by fixing the first-stage decisions in the deterministic model (the investments), and thereafter solving the model using the stochastic operational scenarios. In other words, we use the system typology that the deterministic model version invests in, and test it for the sixty operational scenarios in the stochastic model with no additional investments allowed. Applying the VSS to the *DET* model case results in an infeasible model run. This indicates that the system is not able to cover the demand in at least one of the operational scenarios. The reason for this is the overestimation of the contribution from wind energy in the deterministic version, which leads to insufficient investments in reserve capacity making the energy system unable to meet the demand in operational scenarios with e.g. unfavourable wind and solar availability and/or high electricity and heat demand. This shows the importance of having an adequate representation of short-term solar and wind variability.

The question remains whether our stochastic approach is sufficiently robust to deal with long term persistence of the solar and wind resources, in particular extended periods of low supply. Tsekouras and Koutsoyannis [24] have shown that a significantly positive autocorrelation (Hurst coefficient of 0.84) characterizes long time series of wind and solar radiation in Europe. Zeyringer et al. [57] in a study of the UK, used a high resolution model softly coupled to a TIMES based energy system model to explicitly model impacts of interannual variability of weather. Our approach, based on [22], has the benefit of preserving computational efficiency while allowing for a combined

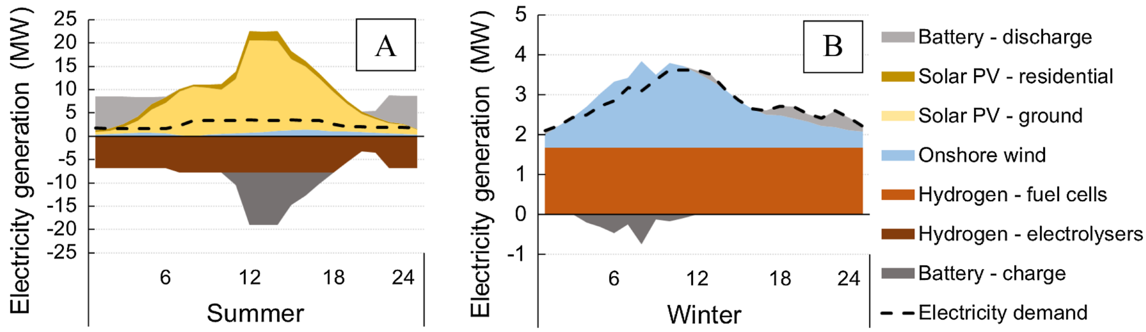

Fig. 7. Examples of system operation in 2050 for a summer (A) and winter (B) day. Note the different scales for electricity generation in A and B.

stochastic treatment of both supply and demand. Inspection of the energy system configurations which emerge as results of the stochastic modelling of Longyearbyen in the present study, see Sections 4.2–4.5, convinces us that they have sufficient energy storage to be robust against periods with persistent low solar or wind resources. However, a more sophisticated treatment of the statistical properties of solar and wind data (e.g. [58]) could be interesting for further development of the model for wider applicability.

4.2. An isolated system (ISO)

The *ISO* case considers a completely isolated Longyearbyen, powered only by locally available renewable energy resources after 2030. By following a stochastic modelling approach, the model finds the optimal system configuration that is able to meet the demand of heat and electricity in all sixty operational scenarios modelled, even those with unfavourable wind and solar conditions.

Large installed capacities of solar and wind as well as a full hydrogen value chain with both short- and long-term energy storage is necessary for a robust and reliable isolated energy system. Fig. 7 shows two examples of system operation in 2050 during a summer day (A) and a winter day (B), which illustrate well the trend seen across the operational scenarios. Detailed results for each scenario is found in Fig. S6 in the supplementary materials.

The fall and winter seasons are important design factors in all model cases, but particularly in the *ISO* case. Due to colder temperatures the demand of heat and electricity are higher during these seasons, the polar night means there is no contribution from solar PV, and although the wind resource is generally higher during fall and winter, there are periods with little or no wind generation. To cover such periods, shown in Fig. 7B, the model uses seasonally stored hydrogen produced in periods of excess electricity (Fig. 7A). The model invests in large amounts of hydrogen storage (31 GWh in 2030 and 22 GWh in 2050), which in addition to covering the demand also needs to compensate for boil-off losses during long-term storage and losses in the fuel cells.

The need for producing and storing large amounts of hydrogen with a relatively low round-trip efficiency, the electrification of heating, and relatively low capacity factors compared to dispatchable technologies call for a large installed capacity of solar and wind. In 2030, the model has invested in 119 MW of solar PV capacity and 126 MW of onshore wind, corresponding to a total capacity of variable renewables ~50 times larger than the peak hourly electricity demand. This leads to periods with large amounts of excess electricity generation. Fig. 7A shows an example of how otherwise curtailed electricity is used in electrolysers for hydrogen production, to be stored for use in other seasons. Here batteries also play a useful role. The model decides to invest in ~10 MW of li-ion battery charging/discharging capacity and ~57 MWh of energy storage in 2030 (~11 MW and ~51 MWh in 2050). In Fig. 7A, one can see that batteries are not only useful for intra-day balancing of demand and supply, but also for balancing the electrolyser loads. By storing a large part of the solar peak in the middle of the day and distributing it to the night, the batteries help the electrolysers to work with a more stable load and avoids investments in large electrolyser capacities otherwise necessary to cover the solar peaks.

In the *ISO* case, all four energy efficiency measures (presented in Section 3.2) are fully implemented, reducing the annual demand of electricity and heat by about 10%. Due to the additional infrastructure needed for power generation, investing in energy efficiency measures is found to be economically attractive in this model case.

Introducing large fractions of variable renewables into a small isolated system could lead to challenges in maintaining grid stability [59–61]. Grid support services traditionally offered by fossil-based technologies, such as frequency and voltage regulation, fault-ride-through and spinning reserve must in this case be supplied through the power electronics of renewables, hydrogen fuel cells and by energy storage technologies. Introducing demand response or installing reserve fossil fuel generators could further help maintain stability in the system. Building such a system could spur further research on its detailed operation.

4.3. Hydrogen import (HYD)

The high investments in storage and generating capacity seen in the *ISO* case would be costly (Fig. 11). This motivates the *HYD* case, which allows import of hydrogen from mainland Norway. The Norwegian power system is characterised by large amounts of hydropower (96% of electricity generation), and has a surplus of about 15 TWh in a normal hydrological year [62]. Utilizing the flexibility of the Norwegian power system, which is many times larger than the Longyearbyen system, could reduce the infrastructure for local power and hydrogen production compared to the *ISO* case. Under the assumption that the imported hydrogen is produced from electrolysis powered by surplus renewable electricity and transported by ship fuelled by hydrogen this model case could still be considered 100% renewable. The amount of imported hydrogen, averaged across all scenarios, is found to be 89 GWh and 60 GWh in 2030 and 2050 respectively. Scenario-specific results for the HYD case are presented in supplementary materials S7.

The 35 NOK/kg import price used in this study [55] is assumed to bear the costs of producing hydrogen in mainland Norway and the transportation to Longyearbyen. Due to the uncertainty associated with this price, we have assessed the sensitivity of the energy system architecture and total system cost by additional model runs with results displayed in Fig. 8. As expected, the amount of imported hydrogen depends strongly on its price. For a price lower than 70 NOK/kg, all of the required hydrogen is imported. For a price of 70 NOK/kg and higher, an increasing share of local hydrogen production is found economically attractive, but at the same time the total share of energy generation from hydrogen fuel cells decreases while wind and solar increase. Producing all hydrogen locally becomes economical only at a very high import price (as shown in Fig. 8). At this point, the HYD case becomes identical to the ISO case. However, a future hydrogen price this high seems very unlikely. Glenk and Reichelstein [63] found a

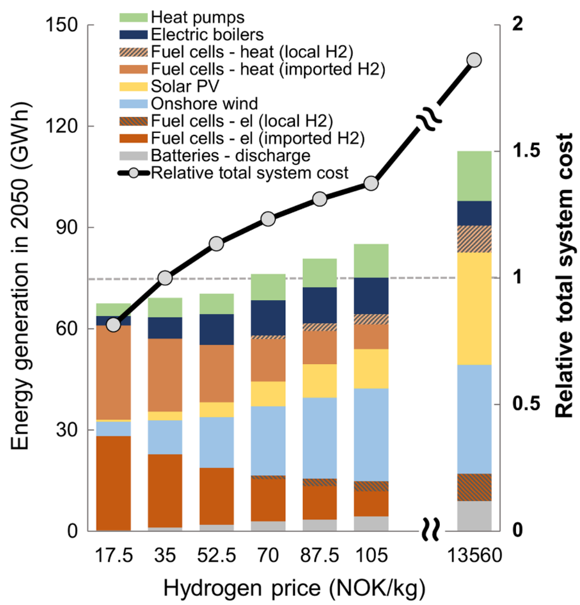

Fig. 8. Sensitivity of energy generation in 2050 (bars) and total system cost relative to a hydrogen price of 35 NOK/kg (line) to the cost of hydrogen.

current break-even price for renewable hydrogen through electrolysis in Germany of 3.23 €/kg (~32 NOK/kg), and predicted a decrease to ~2.3 €/kg (~22 NOK/kg) by 2030.

4.4. Fossil fuels (FOS)

Allowing use of fossil fuels could further reduce the costs of Longyearbyen's future energy system. For a system with no emission restrictions, the model shows a preference towards fossil fuels, investing in new diesel generators, gas cogeneration turbines, pure gas turbines and gas boilers (Fig. 10).

In the unrestricted *FOS* case, moving from coal to natural gas, diesel, and some renewable capacity reduces the CO_2 emissions with a factor of 2/3 from 2015 to about 20 000 ton CO_2 annually from 2030. Fig. 9 shows how the total system cost, and the share of renewables in final energy demand varies with a constraint on CO_2 emissions ranging from no regulations (corresponding to the *FOS* case) to zero emissions (corresponding to the *HYD* case). The system cost first rises gradually as emissions are beginning to be constrained, before increasing rapidly to reduce the last tons of CO_2. This shows that achieving some emission

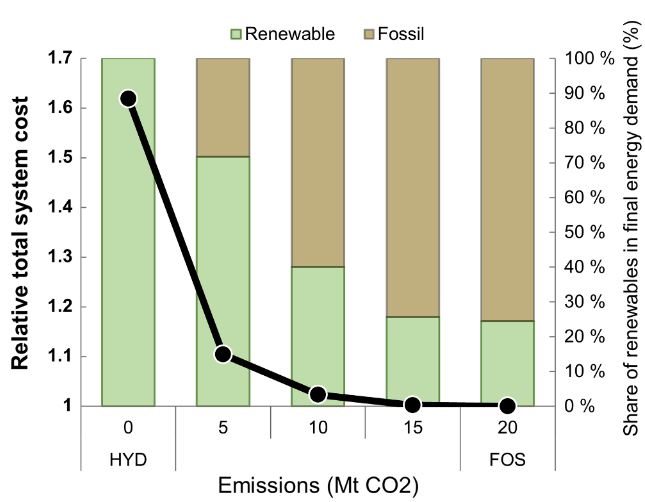

Fig. 9. The impact of constraining emissions on the total system cost and system composition.

reductions is relatively cheap, whereas the last tonnes of CO_2 are very costly to remove.

Allowing for some, but minor emissions could thus be an effective way of considerably reducing the total system cost, and at the same time increase redundancy and possibly reduce local environmental impacts such as land-use and visual impact from large wind turbine installations. As an example, allowing for 25% of CO_2 emissions compared to an unrestricted case (*FOS*) annually would only give about 10% higher total system cost.

4.5. Summary of key results

This section summarises key results on the energy system structure and costs for the four investigated model cases. Tables with detailed results on installed capacity and energy generation as well as scenario specific figures can be found in the supplementary material to this paper.

Fig. 10 shows a comparison of the installed capacities in the *ISO*, *HYD* and *FOS* cases in 2030 and 2050 compared to today's existing capacity. Although the model optimisation suggests investment in new infrastructure already in 2020, it decides to keep the coal-fired power plant until decommission in 2030 in all cases, adding only some minor investments in energy efficiency measures and onshore wind capacity. Since the system composition also does not change much between 2030 and 2050, we only show the installed capacities in 2030 and 2050 in Fig. 10 (complete results are available in the supplementary material).

Electrification of heating is seen in all model cases. Electric boilers, heat pumps and heat from hydrogen fuel cells become the main source for heating in all but the *FOS* model case, where gas boilers provide the majority of heat to the settlement. Large investments in onshore wind are also seen in all model cases. These results are consistent with the Grimsey island study [1], which included fewer options, but also showed that wind and hydrogen could be important parts of Arctic energy systems.

Due to faster cost reductions for solar PV technologies than for wind and despite its lower annual capacity factor, one can see that the share of solar PV in the generation mix increases from 2030 to 2050 in all model cases.

Fig. 10 also shows the total installed capacity of all model cases. As expected, this is very high in the *ISO* case, about seven times larger than the current installed capacity. In all other cases, the total installed capacity is comparable to today's level, as these cases rely on fossil fuels or import of hydrogen.

Since the coal-fired power plant is kept until 2030 in all model cases, this leads to more similar annual system costs between cases for the entire period 2015–2050 than for the period 2030–2050. As the energy system costs are discounted back to 2015, earlier costs play a more important role in the optimisation with respect to total costs than later ones. This explains why the total discounted system costs (Table 4) are more similar in comparison to the large differences seen in the average annual system costs between 2030 and 2050 (Fig. 11).

In Fig. 11, one can see that the *ISO* case has the highest average annual costs, about three times larger than the *HYD* case and about ten times larger than the *FOS* case. This is due to the high requirements for renewable energy capacity, storage and hydrogen infrastructure in an isolated system, which also leads to a very capital-intensive system, where ~84% of the annual costs in 2050 are related to investments. In the *HYD* and *FOS* cases, on the other hand, imports of energy carriers are the driving cost factors, corresponding to ~60% and ~50% of mean annual costs respectively.

The average cost of energy (reflecting both electricity and heat) shown in Table 4 is calculated between 2030 and 2050, thus only taking into account the new energy system in each model case, consistently with Fig. 11. We see that moving from the unconstrained *FOS* case to the 100% renewable *HYD* case almost quadruples the cost of energy, but constraining 2050 emissions to 5000 tonne CO_2/year (~25% of the

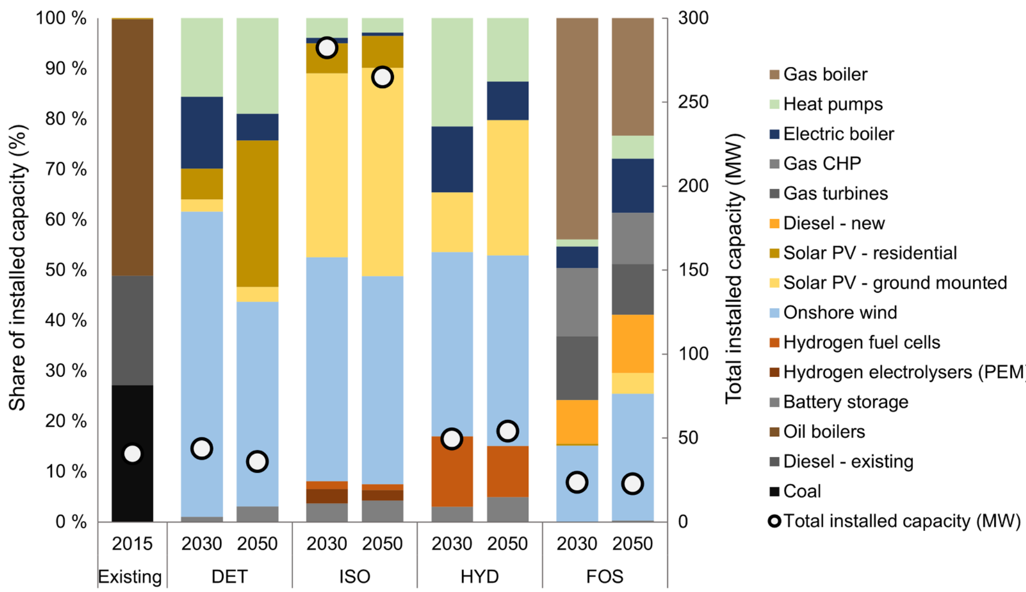

Fig. 10. Share of (bars) and total (markers) installed capacity in all cases. See Table S4 in the supplementary materials for detailed results on installed capacity for all investment periods.

unconstrained 2050 emissions and less than 10% of 2015 emissions) increase the average cost of energy for 2030–2050 by ∼50%.

Even though our model has a relatively high temporal resolution in comparison to other TIMES models, it is worthwhile to validate the model against a less scaled down model. In order to do so, we developed another model version with 672 time-slices, modelling one full week with hourly resolution per season. These two models are essentially equal, with the only difference being the temporal resolution. In order to maintain computational feasibility, we had to reduce the number of stochastic scenarios from 60 to 15. In addition, the scenario generation method selects a full week instead of individual days. We tested the new model with our three main model cases (ISO, HYD and FOS), achieving consistent results in comparison to our 192 time-slice model. When comparing the value of the objective function, the total system cost, all model cases results in a slightly lower total system cost in the 672 time-slice model in comparison to the 192 time-slice model. The HYD scenario has the highest deviation with 5.9%, whereas the ISO case and the FOS case deviates 4.2% and 1.1% respectively. Furthermore, the overall system composition stays the same in both model cases, showing that our scaled down model has an adequate temporal resolution.

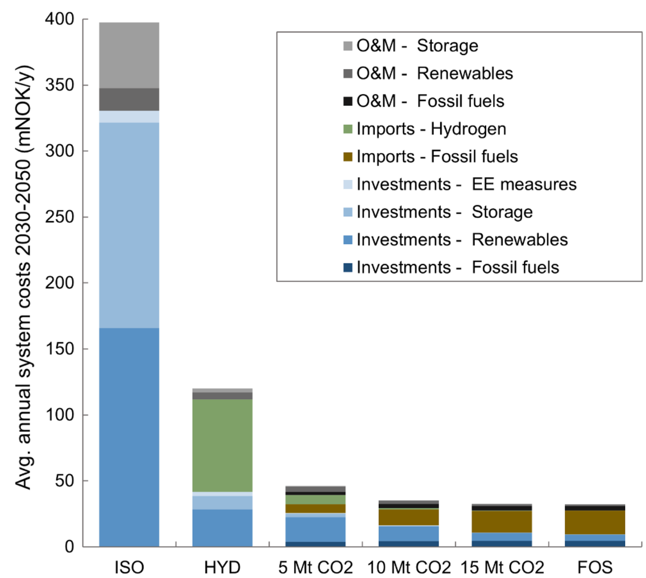

Fig. 11. Avg. annual system cost between 2030 and 2050.

4.6. The role of policy and regulations

Our modelling results suggest that a future energy system in Longyearbyen based primarily on renewable energy sources is feasible, reliable and achievable. Energy efficiency plays an important role, and is a crucial part of our demand projection (hereafter denoted *base*). We envision drastic improvements of energy efficiency in buildings as well as reduced electricity demand due to changes in the industry sector. The demand projection is based on a number of assumptions. If policies fail to address energy efficiency, it could have a great impact on the size and cost of the new required energy infrastructure in Longyearbyen.

To assess the sensitivity of our results, we have investigated the impact of alternative demand projections (shown in Fig. 12). The *status-quo* demand projection assumes no measures are incorporated to reduce energy demand, leaving the demand of heat and electricity on today's level (∼70 GWh heat and ∼40 GWh electricity) until 2050. The *high* demand projection is a more aggressive demand projection, which assumes a doubling of energy demand towards 2050 (∼140 GWh heat and ∼80 GWh electricity). For heat, this would mean a continuation of the trend seen between 2000 and 2010 (continuous line in Fig. 3). This would be consistent with a doubling of the population to about 4000 residents in 2050 and assuming that the specific heat demand (kWh/m^2 y) remains on today's levels. In addition, it assumes an increase in

Table 4
Key economic results.

Key economic results	ISO	HYD	5 Mt CO_2	10 Mt CO_2	15 Mt CO_2	FOS
Total discounted system cost (bNOK)	4.93	2.21	1.51	1.40	1.37	1.36
Cost of energy (2030–2050 avg.) (NOK/kWh)	5.73	1.73	0.67	0.51	0.47	0.46

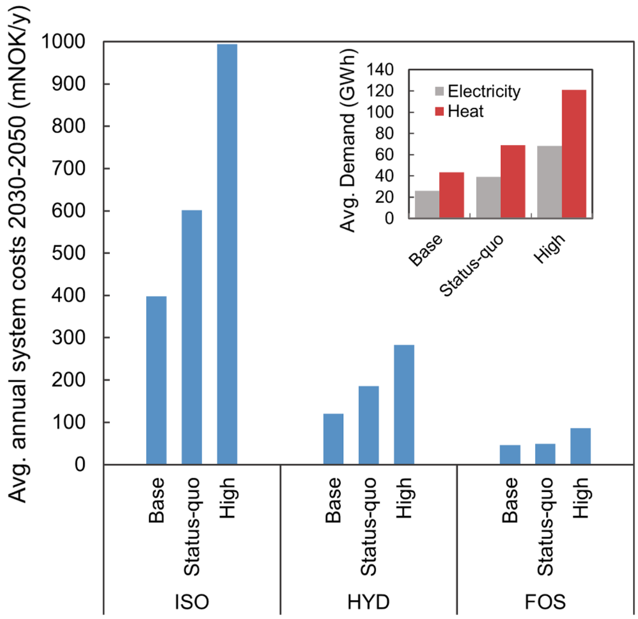

Fig. 12. Sensitivity of annual system cost in 2050 to alternative demand projections. The average energy demand (electricity and heat) between 2030 and 2050 for the alternative demand projections is shown in the fig. inset.

activities e.g. within tourism and/or research, as well as a large degree of electrification (e.g. of the transport sector) that leads to a doubling of the electricity demand. A projection with significantly lower future energy demand than the *base* scenario is not considered realistic and therefore not assessed.

Fig. 12 shows that an increase in energy demand gives significantly more expensive systems in all model cases. The *ISO* case is the most sensitive to changes in energy demand, linearly increasing its annual system cost by 3.7 mNOK per GWh of increased energy demand. This is expected due to the extra infrastructure needed to cover the higher energy demand. The *HYD* and *FOS* cases are less sensitive to changes in the demand, due to the availability of imports of energy carriers, and have an increase in annual system costs of only 1.0 and 0.3 mNOK per GWh respectively.

The selection of discount rate is expected to influence particularly the balance between capital and operation intensive technologies. We have tested all cases with a 2% and 6% discount rate in addition to the base case 4%. The results displayed in Fig. 13, show that these changes of discount rate have a discernible but not drastic impact on the results for Longyearbyen. The overall composition of the system stays roughly the same in all model cases, although a discount rate of 2% favours investments in renewable capacity (high upfront investment, but low operational costs), while a 6% discount rate favours investments in fossil fuels or imported hydrogen (lower investments, but higher running costs).

An advantage of a renewable based system is its modularity, which means that one can incorporate units into the system one at a time. This can help sizing the system according to the actual development of a highly uncertain future energy demand. Furthermore, a gradual transition to a system based on renewables, while phasing out the coal-fired power plant in a controlled manner, could ease the operation and keep security of supply in place. Modularity also improves system reliability, as it is highly unlikely that several units fail at the same time.

For future work, the TIMES model of the settlement could be expanded to also include the transportation sector. There are almost as many snowmobiles as people and about 1500 cars in the settlement [37]. Tourism is likely to lead to an increased use of tourist ships and visits from large cruise ships. This puts sustainable tourism on the agenda. Given energy demand projections for these sectors, an expanded version of the present model could evaluate the potential of electrification and the use of hydrogen in the transport sector, enabling cross-sector synergies and potentially deeper decarbonisation of the settlement.

Environmental aspects not captured by this modelling study should be included in planning and policy making. As an example, the installation of new infrastructure, e.g. onshore wind turbines and extensive areas for solar panels, can disturb existing habitats in an already constrained Arctic ecosystem and their impact should be carefully considered before installation. The broader environmental impact of lithium ion batteries should also be further assessed. Not only in terms of greenhouse gas emissions and energy use in the production phase, but also in terms of lifecycle impacts including materials usage, toxicity and the social risk particularly related to the mining of cobalt [64,65].

We recommend that new policies ensure that energy efficiency is prioritised, and that a new system should include renewable generating capacity, energy storage, electrification of heating, and imports of hydrogen, in this case most likely from mainland Norway. Fossil fuel backup capacity could be installed to reduce costs and increase security of supply in the settlement. A renewable based energy system in an Arctic location such as Longyearbyen could also be a valuable research

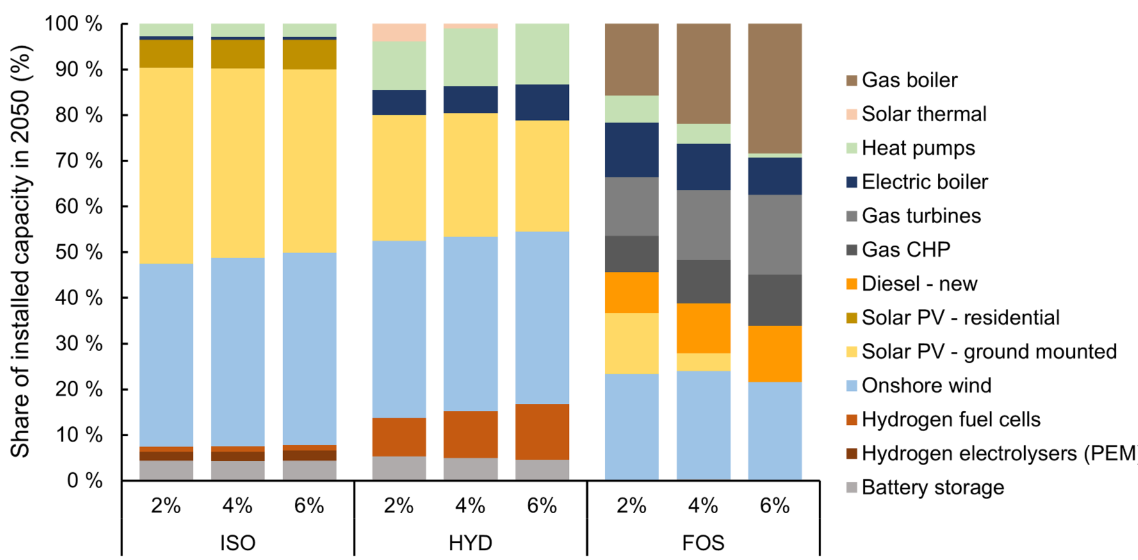

Fig. 13. Sensitivity of the key model results on the discount rate.

opportunity, and an example for others to follow.

The approach and the findings from this study should be relevant for other Arctic communities. Although wind and solar resources vary from place to place and are likely to influence the structure of the resulting optimal energy system, most of the properties of the energy system components studied here should be almost directly applicable to studies of other locations.

5. Conclusion

Three main conclusions can be drawn from this work. First, incorporating an adequate modelling of the variability of renewables is highly important for ensuring the robustness of modelling studies in cases where a significant part of the energy supply is based on variable renewables. Handling this variability is particularly important when security of supply is of highest importance, such as in the case of a remote Arctic settlement. A careful representation of the stochastic properties of the solar and wind resources is recommended.

Second, the detailed and realistic case study shows that Longyearbyen has the potential of being supplied by an energy system based primarily on renewable energy sources with wind and solar as both complementary and critical contributors. The potential of harnessing wind and solar in Arctic locations is significant, and when utilised together they have beneficial complementary properties. Energy efficiency is also of high importance, and policies and regulations should be directed towards improving energy efficiency and reducing energy usage. An isolated system based only on locally available renewable resources is technically feasible, but requires high installed capacities, and is found to have annual system costs about three times larger than a case where import of hydrogen is allowed. Allowing for a limited fraction of the energy supply to come from fossil fuel use could significantly reduce system costs, increase robustness and system reliability while still obtaining major reductions of emissions compared to cases where the use of fossil fuels is unconstrained.

Finally, the developed model tool could easily be expanded to optimise an extended energy system, which not only supplies the settlement, but also tourist ships and other transportation needs. It could also be adapted to other remote settlements with other starting and boundary conditions. While specifics including costs of hydrogen import can be expected to vary with location, one may speculate that the major building blocks of the emerging system including wind, solar and hydrogen storage will remain. These technologies in contrast to geothermal and carbon storage have the advantage of being generic and not so dependent on costly investigations of local conditions.

Acknowledgements

The motivation to conduct this study came after a summer course on Sustainable Arctic Energy Exploration and Development at the University Centre in Svalbard. This course included a group project led by the first author of the present study, where a simple conventional deterministic TIMES-model of the energy system in Longyearbyen was developed and analysed. The results from this group work (also partly reported in [66;67]) indicated that a system based mainly on solar and wind in combination with batteries could be a reliable and cost-effective solution. In order to set these early results on a firm basis, a more detailed modelling study was required.

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Declaration of Competing Interest

The authors have no competing interests to declare.

Data accessibility

Solar and wind data used in this this study are publicly available and can be retrieved from https://www.renewables.ninja/. Costs and technological parameters used as input to the model are given in the supplemental materials (Table S1).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2019.114079.

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