



Research Centre on
ZERO EMISSION
NEIGHBOURHOODS
IN SMART CITIES

NEIGHBOURHOOD BUILDING STOCK MODEL FOR LONG-TERM DYNAMIC ANALYSES OF ENERGY DEMAND AND GHG EMISSIONS

General model description and case studies

ZEN REPORT No. 2 – 2018



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Neighbourhood building stock model for long-term dynamic analyses of energy demand and GHG emissions. General model description and case studies

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Abstract

How should sustainable neighbourhoods be designed to reduce greenhouse gas emissions towards zero? What kind of information does decision makers need to make solid future plans on the neighbourhood level? A detailed understanding of a building stock's characteristics and development over time is an underlying premise for reliable long-term building stock energy analyses. On the neighbourhood level, the building stock can be studied in large detail. Interactions between buildings and the local energy system can be analysed considering energy need, supply, local generation and local storage. Hourly resolution is needed to estimate peak heat and electricity loads in the neighbourhood. Further, greenhouse-gas (GHG) emissions resulting from the energy use in the buildings in the neighbourhood can be estimated by use of carbon intensities for the various energy carriers used in the neighbourhood.

This report is deliverable D1.2.2 and a part of FME ZEN Work Package 1 Analytic framework for design and planning of zero emission neighbourhoods (ZEN). The goal for WP 1 is to develop definitions, targets and benchmarking for ZEN, based on customized indicators and quantitative and qualitative data. Additionally, life cycle assessment methodology for energy and emissions at neighbourhood scale will be developed, as well as a citizen-centred architectural and urban toolbox for design and planning of ZEN.

A dynamic building stock model has been developed for energy- and GHG-emission scenario analyses of neighbourhoods. The model is generic and flexible and can be used to model any neighbourhood where building stock data is available. It makes use of a description of the current stock, as well as plans for construction, demolition and renovation activities in the neighbourhood. If plans are not available, the model may simulate stock activities by use of probability distributions. The neighbourhood building stock is segmented by use of archetypes defined by the buildings' age, renovation state and floor area classes. Examples are grouping the two floor area types single family houses (SFH) and terraced houses (TH) together into a detached dwellings floor area class or grouping primary schools and secondary schools into a floor area class called "school buildings". Hourly energy demand is estimated using delivered energy intensity profiles given for different archetypes of buildings or empirical data. Any number of different energy carriers and purposes can be defined and monthly or yearly carbon emission intensities can be given for each individual carrier. This serves as a basis to estimate hourly, monthly or yearly delivered energy and GHG emissions for a given neighbourhood under study.

Two cases are analysed in this report: i) a hypothetical case of an imaginary neighbourhood consisting of apartment block (AB) and SFH dwellings, and ii) the Gløshaugen campus of the Norwegian University of Science and Technology (NTNU). Gløshaugen campus is a neighbourhood that has a high complexity of floor area types and usage. The purpose of the two very different case studies is not to provide reliable case studies at present, but to demonstrate how the model is capable of long-term analyses of both homogenous and complex neighbourhoods in order to offer detailed understanding of possible future hourly energy use and GHG emissions.

For the hypothetical case, the model describes how the energy-efficiency of the stock improves over time due to renovation and demolition of older buildings and construction of new buildings with low energy need. The baseline scenario estimated annual delivered energy decrease from 150 kWh/m² per

year at present to 90 kWh/m² per year in 2070. Estimated GHG emissions decrease by 46% from 37 kton CO₂-eq/year at present day to about 20 kton CO₂-eq/year in 2070. Additionally, an advanced renovation scenario assuming that buildings being renovated have a higher probability of reaching better energy standards shows that the estimated annual delivered energy and GHG emissions will decrease faster in this scenario than the baseline scenario. Estimated annual delivered energy is 2% lower in 2025, 4% lower in 2030 and 7% lower in 2040 in the advanced renovation scenario than in the baseline scenario. Looking at aggregated GHG-emissions for the whole period, an estimated reduction of 8% from present day to 2070 compared to the baseline scenario is observed. Annual GHG emission gains compared to the baseline scenario are peaking around 2050 with 12% annual reduction of GHG emissions before natural renovation in the baseline scenario starts to catch up with the advanced renovation scenario. This is due to the fact that buildings in the baseline scenario go through renovation for the second time and reaches the third renovation state between 2050 and 2070. Constant monthly carbon intensities per energy carrier are assumed in the analysis, but it is likely that future monthly carbon intensities will change over the years of the period. A decrease in carbon intensities would lead to a further decrease in annual emissions over time.

The neighbourhood building stock at NTNU campus Gløshaugen has a highly complex composition with 46 existing buildings (in total 300 000 m² heated floor area) providing a large variety of functions related to education and research. 17 different floor area types are identified and distributed to 7 floor area classes. The planned future expansion of the campus is represented through construction of 120 000 m² heated floor area before 2030. Average delivered energy intensity profiles per floor area class are modelled based on empirical data by using the simulation tool IDA ICE. The simulated profiles are used as energy model input. There is only one available energy profile per floor area class, regardless of the construction year and renovation state. Hence, the model is not able to estimate reductions in energy demand due to energy-efficiency of the stock through renovation and demolition of existing inefficient buildings or construction of new energy-efficient buildings. Carbon intensities are estimated monthly for district heating and grid electricity. Hourly and monthly peak loads, delivered energy and GHG-emissions are estimated for the whole neighbourhood at present year. The estimated long-term development in delivered energy and GHG emissions for Gløshaugen follows the stock development closely. This shows the weakness of using average profiles that do not reflect the differences in energy-efficiency state for buildings that are constructed in different periods or in different renovation states. A more detailed database of delivered energy intensity profiles is needed to create a more reliable long-term analysis taking into account stock activities and changes in the building stock characteristics.

By changing different input parameters in the building stock, energy and GHG-emission model, different scenarios of future pathways can be studied. Various possible energy-efficiency measures can be analysed and compared with each other. This flexibility is a strength of the model as it makes analysing complex neighbourhoods possible.

The model allows for creating roadmaps that decision makers can use when planning future development of neighbourhoods with building stocks and energy supply systems. The hourly time resolution makes it useful for electricity and district heating companies when planning future grid capacity need. The ability of the model to estimate and compare long-term changes in neighbourhood GHG emissions between scenarios makes it useful for decision makers aiming for future emission reductions.

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Abbreviations

AB – Apartment block

COP – Coefficient of performance

IDA ICE – Simulation program for energy use in buildings

DH – District heating

GHG – Greenhouse gas

GWP100 – Global warming potential over a 100-year time interval

HP – Heat pump

MFH – Multi family house

N - Neighbourhood

PV – Photovoltaics

SFH – Single family house

WP – Work package

ZEN – FME Research Centre on Zero Emission Neighbourhoods in Smart Cities

Variables and parameters

A – Heated floor area

a – Average heated floor area

B – Building stock

b – Building

B_{dem} – Demolition activity

B_{new} – Construction activity

B_{ren} – Renovation activity

D - Floor area density

E – Delivered energy

E_g – Energy generation

E_n – Energy need

E_s – Energy storage

E_i – Energy intensity

G – GHG emissions

I – Carbon intensity

L – Load profile

R_c – Renovation cycle

S – Coincidence factor

Indices

c – Cohort (construction period of buildings)

e – Energy carrier

r – Renovation state (original state, standard renovation, advanced renovation)

u - Unit

v – Variant (variants of archetypes depending on measures)

y – Floor area type

z – Floor area class

1. Introduction

The building sector represents 40% of the total final energy consumption and can make a crucial contribution to GHG emission mitigation (Buildings Performance Institute Europe, 2011). To be able to utilize possible energy demand reduction and GHG emission mitigation potentials, detailed knowledge about the building stock system is needed, from the national or international level, to neighbourhood building stocks and individual buildings.

The energy use in national and urban building stocks has been studied in a range of publications (e.g. Buildings Performance Institute Europe (2011), Ürge-Vorsatz et al. (2012), Berardi (2017), Choudhary (2012), Cuerda et al. (2014), Heeren et al. (2013), Sandberg et al. (2017)). Furthermore, significant effort has taken place to analyse the potential energy savings in individual buildings, e.g. through the Research Centre on Zero Emission Buildings (ZEB) (www.zeb.no). In between the level of the individual buildings and the aggregated urban or national building stocks lies the neighbourhood level. At this level, it is possible to analyse the building stock in large detail, but at the same time to take into consideration interaction between buildings located nearby each other and local solutions for energy generation and storage. This is the background for the Research Centre on Zero Emission Neighbourhoods (ZEN) (www.zenresearchcentre.com), which started in 2017 and builds on the research activities carried out in ZEB.

How should the sustainable neighbourhoods of the future be designed, built, transformed and managed to reduce their greenhouse gas emissions towards zero? What kind of information do the various decision-makers need, and how can we best provide and tailor this information by use of a neighbourhood dwelling stock energy model?

Previous studies, such as Sandberg et al. (2016) and Sandberg et al. (2017), has shown the need for a detailed understanding of the present building stock and its long-term evolution when performing energy analysis of a stock at the national level. Næss (2017) used the same methodology to study the dwelling stock and perform energy analysis for the municipality of Trondheim. The stock composition in Trondheim was found to vary strongly between different subareas of the city, and hence suggests that a detailed bottom-up approach might be suitable for modelling a neighbourhood.

Sandberg et al. (2016, 2017) and Næss (2017) estimated the yearly energy demand by use of average yearly energy demand intensities. On a neighbourhood level, it is important to estimate the hourly energy demand to find the peak load and hence the required capacity of the grid. Furthermore, to complete the analysis, service buildings should be included, in addition to residential buildings. Finally, estimation of GHG emissions resulting from energy use should be estimated to be able to evaluate the impacts of the energy use in the neighbourhood.

The Research Centre on Zero Emission Neighbourhoods in Smart Cities (FME ZEN) will enable the transition to a low carbon society by developing sustainable neighbourhoods with zero greenhouse gas (GHG) emissions. The Centre will speed up decarbonisation of the building stock (existing and new),

use more renewable energy sources and create positive synergies among the building stock, energy, ICT and mobility systems, and citizens.

The main objective of the FME ZEN is:

- *Developing competitive products and solutions that will lead to realization of sustainable neighbourhoods that have zero emissions of greenhouse gases related to their production, operation and transformation.*

Which leads to the main research question or the research centre:

- *How should the sustainable neighbourhoods of the future be designed, built, transformed and managed to reduce their greenhouse gas emissions towards zero?*

Work package 1 (WP1) among others has the more detailed research question:

- *What kind of information do decision makers at all levels need, and how can we produce and customize this information?*

Within the context of the FME ZENWP1, a dynamic neighbourhood building stock energy model has been developed. The model studies the development over time in the neighbourhood's building stock size and composition of building typologies as well as the energy-related features of the individual buildings and on the neighbourhood level. The model is generic and can be applied to any neighbourhood. In this report, the principles of the model are described in detail, and it is applied to two case studies for exemplification; a hypothetical case and the Norwegian University of Science and Technology's (NTNU) campus Gløshaugen.

2. Methodology

2.1 The neighbourhood building stock model

2.1.1 Model fundamentals

The neighbourhood building stock model describes the long-term dynamic development in a neighbourhood's building stock B and the construction, renovation and demolition activities in the system. The model is based on the principles of material flow analysis (Brunner & Rechberger, 2004). A conceptual outline of the model is given in Figure 1.

The model uses a detailed description of the initial stock at the starting year of simulation $B(t_0)$ together with given or assumed plans for future construction B_{new} . Demolition B_{dem} and renovation B_{ren} are either estimated by use of plans or simulated based on input probability distributions. A full description of the equations used in the stock model is given in Appendix A.1.

The building stock is segmented into different archetypes based on construction periods (cohort) c , floor area classes z , renovation states r . For each year in the given modelling period, the model calculates the heated floor area A for the given archetypes. Buildings can move from one archetype to another over time, as they are renovated according to plans or simulation.

Renovation of a building can take place multiple times throughout the building's lifetime. Various types of renovation activities occur at different intervals. When simulating renovation activity by use of probability functions in the model, the renovation cycle R_c represents the average time between renovation of a given type. How renovation activity is defined and what the corresponding length of the renovation cycle should be is case-specific. For instance, the 20-year cycle could be applied for replacement of appliances (e.g. boilers), the 30-year cycle for replacement of construction elements such as windows or roofs and the 40-year cycle for deep renovation of facades (Sandberg et al., 2014).

The energy profile of a given building can change when a building is renovated. The model allows up to three different renovation states to be used for a given renovation cycle for each building. The energy-efficiency state of a given building is dependent on its archetype. Variants can be given for different archetypes and represents smaller measures such as instalment of heat pumps or changing user equipment. The 20-year and 30-year cycles can for instance be represented in the model as a change in variant for a given building.

The bottom level of the model are the units U . Each building consists of one or several units. A unit can typically represent for instance a dwelling, an office or a grocery store. Each unit object belongs to a building b , cohort c , renovation state r , variant v and a floor area type y . The cohort is defined by construction period. Furthermore, each floor area type belongs to a floor area class z that represents a group of floor area types with similar functionality and energy use through the year. These model levels are given as arrays as shown in Figure 2.

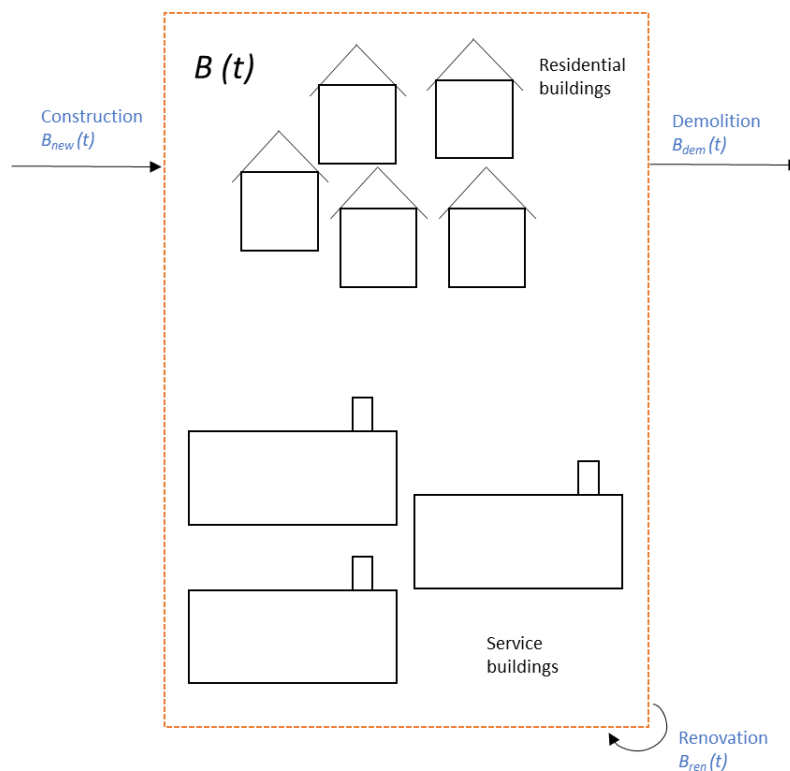


Figure 1: Conceptual outline of the dynamic neighbourhood building stock model.

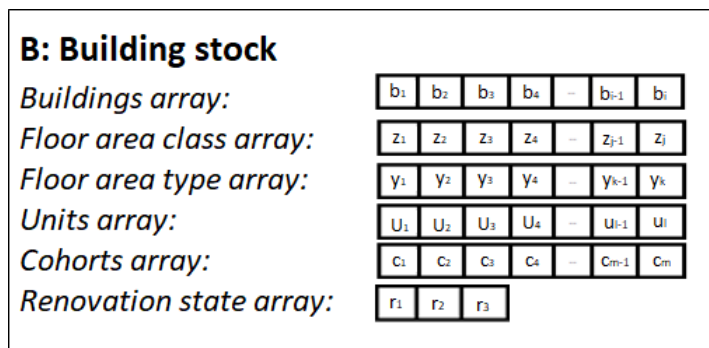


Figure 2: The different levels of the building stock model.

Buildings in a stock that have only one floor area type are defined as simple buildings, while buildings that have several floor area types are defined as complex buildings, as shown in Figure 3. An example of a simple building is a single family dwelling, where the whole building is represented by the class “single family house”. An example of a complex building can be a university building consisting of different user defined floor area types like offices, hallways, auditoriums, shops and restaurants. Similar floor area types are grouped together into floor area classes. This is done to allow for floor area types of similar functionality and energy use characteristics to be modelled together by using the same hourly profiles for delivered energy. The model allows for empirical or simulated delivered energy profiles to be used.

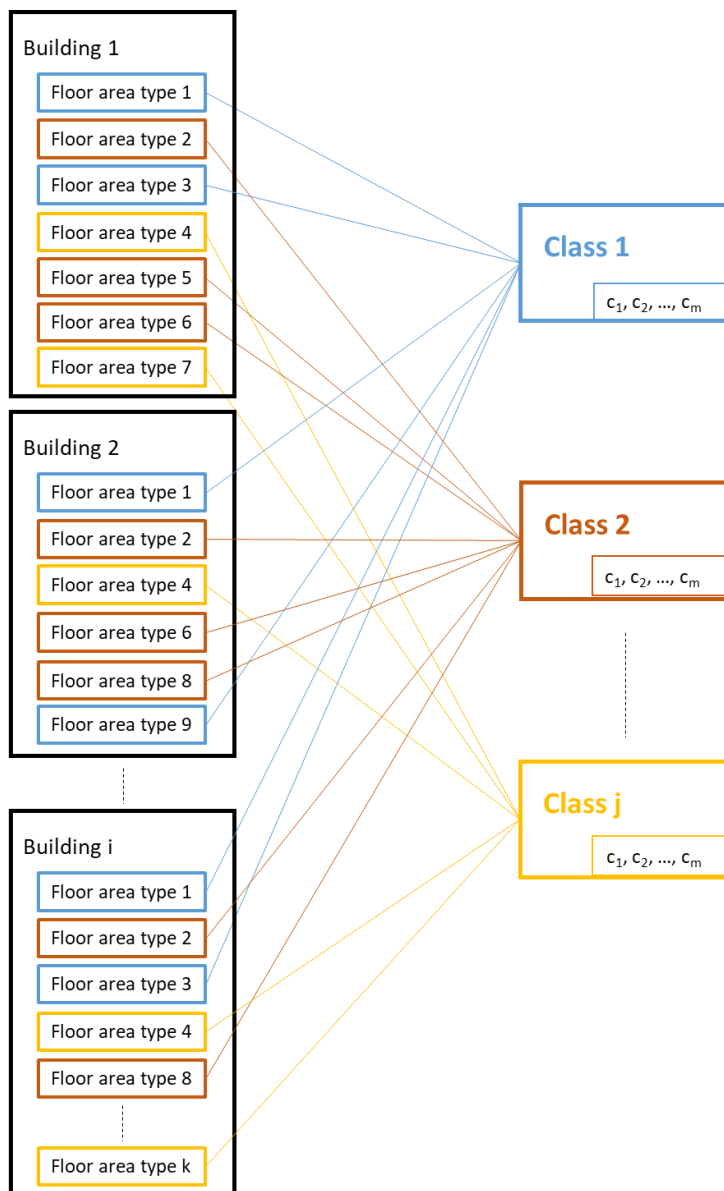


Figure 3: General example of the model structure for complex buildings.

2.1.2 Simulation of system activities

The model uses yearly time steps and calculates the state of the neighbourhood building stock for each year in the modelling period. If there are no events scheduled to happen, the system state is equal to the state of the previous year. If events are scheduled, e.g. construction, renovation or demolition, the model calculates a new system state for the given year. Changes in the system are tracked over time.

Specific plans for renovation and/or demolition can be applied in the model. If specific plans are not available, renovation and/or demolition can be simulated. This happens by generating random stochastic numbers in Matlab and using cumulative probability distributions. Starting with the initial state of the stock given at the first year of the modelling period, discrete-event simulation is used to simulate later changes in the system.

Normal probability distributions are assumed when simulating renovation activity. Distribution parameters standard deviation σ and mean μ are given as inputs per floor area class, and events are simulated accordingly. For complex buildings, the model assumes that the floor area class with the largest share of the heated floor area is the major class. The corresponding input parameters are used during the simulation.

Demolition activities can be simulated in a corresponding way. The model allows for either a normal distribution or a Weibull distribution. The demolition probability distributions are specified for each of the two categories residential floor area classes and service building floor area classes. If a normal distribution is chosen, μ and σ is given in input, but if a Weibull distribution is given the average lifetime, period of years without demolition γ , scale parameter a and shape parameter b needs to be input. Literature suggests to use the Weibull distribution when simulating building demolition (Sandberg, Sartori, & Brattebø, 2014). Bohne et al. (2006) estimated the average lifetime of Norwegian dwellings to be 126 years. It is, however, likely that the average lifetime of service buildings is different from residential buildings and this input parameter should be considered carefully before running simulations involving service buildings. Sensitivity analyses could also be included to evaluate the importance of the uncertainty in this parameter.

It is worth noting that the stochastic simulation of future system activities (new construction, renovation and demolition) works best when the number of buildings in stock is relatively large. When analysing a small neighbourhood system with a low number of buildings in its stock, it is recommended to give future system activities as input manually rather than by stochastic simulations.

2.2 Energy modelling of a neighbourhood

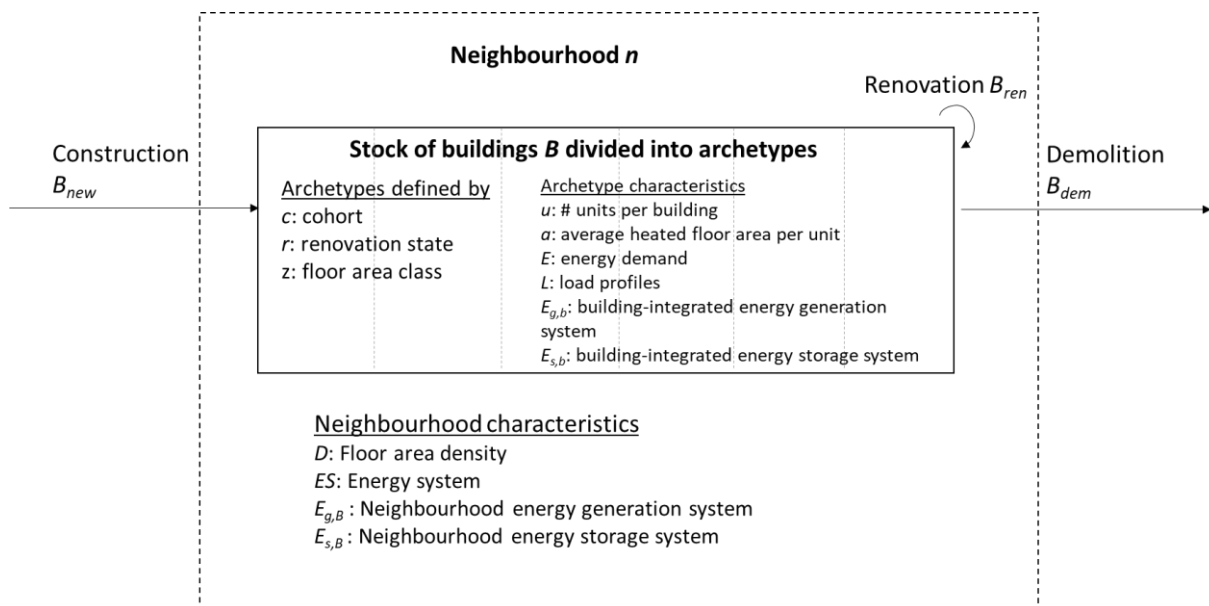
2.2.1 Model fundamentals

The dynamic neighbourhood stock model described in chapter 2.1 provides a solid foundation for detailed long-term energy analysis for a given neighbourhood building stock. All energy carriers in the system are defined as model input, as shown in the example in Table 1. The user can define the numbers of carriers and the energy use purposes. A purpose can for instance be electricity specified for lighting or electricity specified for heating. The share of delivered energy that is electricity going to appliances is given as α .

Hourly load profiles can be given on the archetype level as energy intensity profiles or as empirical energy profiles on the building level. The delivered energy for all energy carriers is aggregated for each year in the model period based on the state of the system. Furthermore, building- or neighbourhood-specific hourly energy generation profiles and parameters for energy storage can be included in the analysis. Finally, the model estimates the aggregated load profiles for delivered energy to the whole neighbourhood. The energy model for a general neighbourhood is presented in Figure 4 and Figure 5. A full description of equations used in the energy model is given in Appendix A.2.

Table 1: Example of an energy carrier's database given as model input.

ID	Name	Text used in energy profile input column (E.G. IDA ICE)	Comment	Is electricity	Share used for heating
[#]	[string]	[string]	[string]	{0,1}	[0-1]
1	CHP Electricity	CHP electricity, W	IDA ICE	1	0
2	DH cooling	District cooling, W	IDA ICE	0	1
3	DH heating	District heating, W	IDA ICE	0	1
4	DHW	Domestic hot water, W	IDA ICE	0	1
5	EL cooling	Electric cooling, W	IDA ICE	1	1
6	EL heating	Electric heating, W	IDA ICE	1	1
7	EL equipment, tenant	Equipment, tenant, W	IDA ICE	1	1
8	EL equipment, facility	Equipment, facility, W	IDA ICE	1	1
9	Fuel cooling	Fuel cooling, W	IDA ICE	0	0
10	Fuel heating	Fuel heating, W	IDA ICE	0	0
11	Heating, tenant	Heating, tenant, W	IDA ICE	0	0
12	HVAC aux	HVAC aux, W	IDA ICE	1	1
13	EL, lighting tenant	Lighting, tenant, W	IDA ICE	1	1
14	EL, lighting facility	Lighting, facility, W	IDA ICE	1	1
15	PV production	PV production, W	IDA ICE	1	0
16	Wind turbine product	Wind turbine production, W	IDA ICE	1	0
17	EL, Equipment	Equipment, W	IDA ICE, Nesgård & Ngo	1	0
18	EL, Lighting	Lighting, W	IDA ICE, Nesgård & Ngo	1	0
19	Heating	Local heating units, W	IDA ICE, Nesgård & Ngo	0	1
20	DH cold	District heat_cold, W	IDA ICE, Nesgård & Ngo	0	1

**Figure 4: System description of the neighbourhood model.**

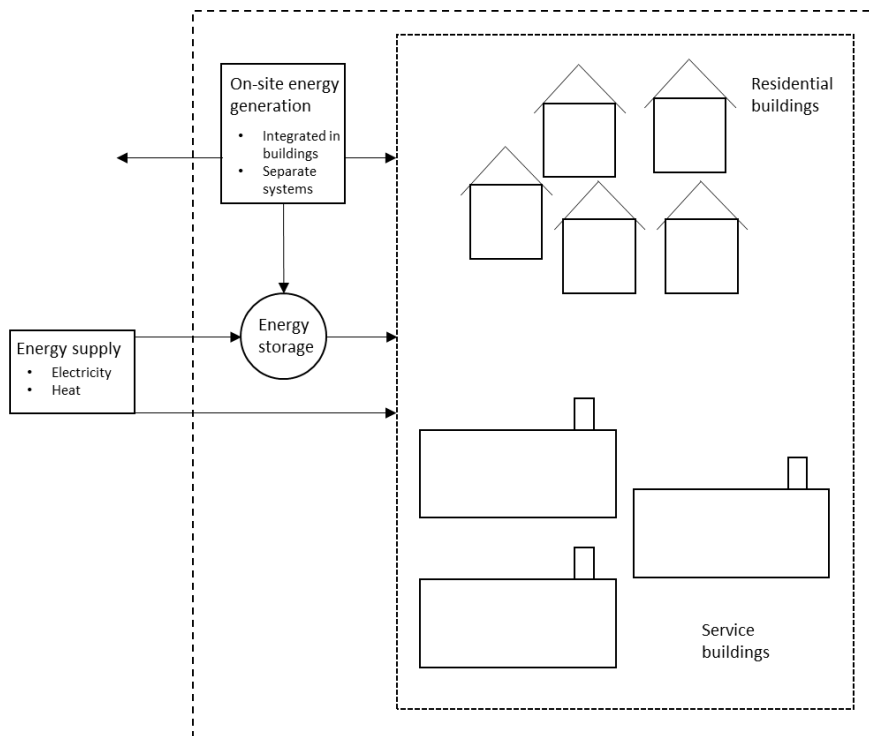


Figure 5: Conceptual outline of the energy model.

2.2.2 Coincidental analyses

When aggregating the same archetype delivered energy intensity profiles for a number of buildings, it is likely that the model will overestimate the power peaks in the neighbourhood. This is because the actual peaks of individual buildings are unlikely to happen during the same hour. For energy planning purposes, it is important to estimate the real peak loads. Coincidental analyses can be used to estimate the actual power peak of the neighbourhood. Coincidence factors below 1.0 indicate that the individual peak loads does not appear simultaneously across the buildings. An example of two hourly delivered energy profiles that do not have peak loads in the same hour is given in Figure 6 (Nord, 2014). The corresponding power peaks are given as $P_{1, max}$, $P_{2, max}$ and the total of the two $P_{tot, max}$. Further equations describing the coincidence factor is given in Appendix A.4.

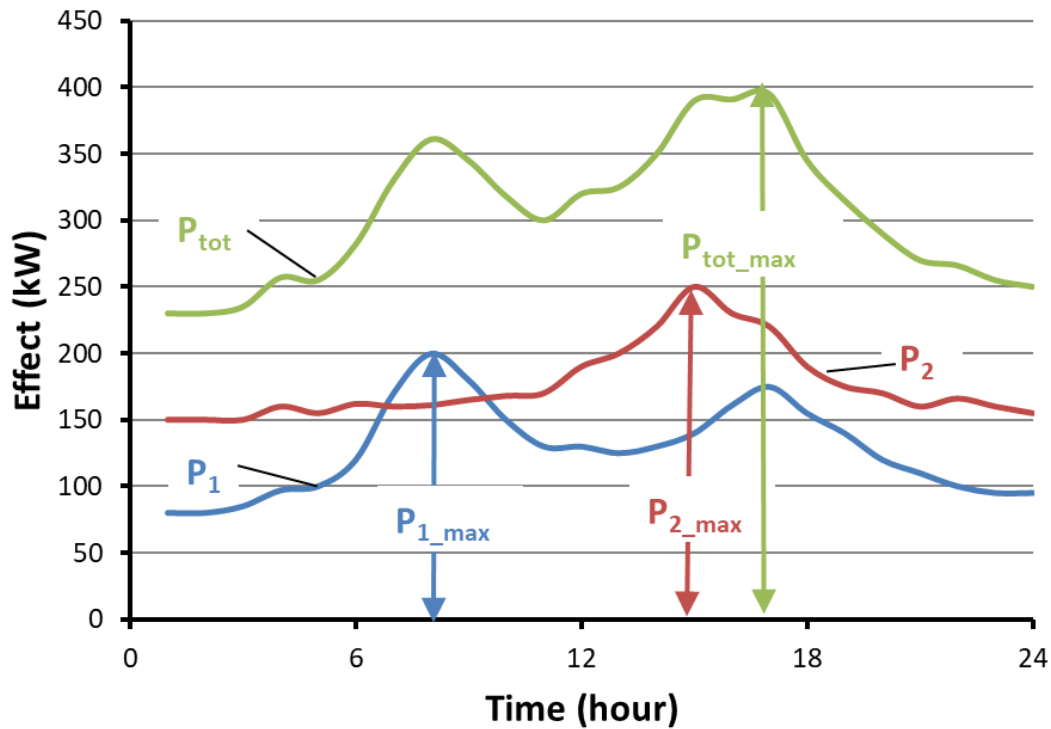


Figure 6: Example of hourly delivered energy curves P_1 and P_2 and the total delivered energy $P_{tot,max}$ (Nord, 2014).

2.3 Modelling of greenhouse gas emissions

Greenhouse gas emissions G are estimated based on the outputs from the energy model and input time series for carbon intensities I . The model allows for carbon intensities changing over time and given either per year or per month for each energy carrier. Equations used in the GHG emission analyses are presented in Appendix A.3.

Estimated GHG emissions per energy carrier e are calculated hourly, monthly and yearly for the complete modelling period. Results are also differentiated into archetypes for each time step. This allows for tracking emissions for different stock segments over time and comparing different measures targeting specific archetypes.

2.4 Case description: Hypothetical case

A hypothetical case was created to test the model. Selected building typologies from the EPISCOPE project described in Brattebø et al. (2016) and shown in Figure 7 are used to divide the stock. The typologies are defined by dwelling type and construction period. For each typology, three renovation states are described: original state, standard renovation and advanced renovation.

	Region	Construction Year Class	Additional Classification	SFH	TH	MFH	AB
				Single-Family House	Terraced House	Multi-Family House	Apartment Block
1	National (not region specific)	... 1955	generic	 NO.N.SFH.01.Gen	 NO.N.TH.01.Gen		 NO.N.AB.01.Gen
2	National (not region specific)	1956 ... 1970	generic	 NO.N.SFH.02.Gen	 NO.N.TH.02.Gen		 NO.N.AB.02.Gen
3	National (not region specific)	1971 ... 1980	generic	 NO.N.SFH.03.Gen	 NO.N.TH.03.Gen		 NO.N.AB.03.Gen
4	National (not region specific)	1981 ... 1990	generic	 NO.N.SFH.04.Gen	 NO.N.TH.04.Gen		 NO.N.AB.04.Gen
5	National (not region specific)	1991 ... 2000	generic	 NO.N.SFH.05.Gen	 NO.N.TH.05.Gen		 NO.N.AB.05.Gen
6	National (not region specific)	2001 ... 2010	generic	 NO.N.SFH.06.Gen	 NO.N.TH.06.Gen		 NO.N.AB.06.Gen
7	National (not region specific)	2011 ...	generic	 NO.N.SFH.07.Gen	 NO.N.TH.07.Gen		 NO.N.AB.07.Gen

Figure 7: Typology matrix for the Norwegian building stock in the Episcopa/Tabula project (Brattebø et al., 2016).

Stock, energy and GHG emission intensity input parameters and assumptions are described in the following subchapters.

2.4.1 Stock input

Construction periods are assigned to cohorts in accordance with the typology matrix from

Table 2.

Table 2: Definition of cohorts for the hypothetical case.

Cohort ID	From Year	To Year
[#]	[year]	[year]
0	0	1800
1	1801	1955
2	1956	1970
3	1971	1980
4	1981	1990
5	1991	2000
6	2001	2010
7	2011	2020
8	2021	2070

Based on this a building stock consisting of AB01-07 and SFH03 has been modelled in the hypothetical case, as simulated hourly energy profiles are available for these segments of the stock. The assumed construction of dwellings in the neighbourhood stock of the hypothetical case is described in Table 3. For each given construction period the input buildings are distributed equally to each year in the period. Average heated floor area per unit corresponds with the national average for the given construction period found in Brattebø et al. (2016).

Table 3: Building stock input details.

Construction period [years]	Cohort	Building floor area type	Number of buildings	Number of units per building	Average heated floor area per unit [m²]	Average heated floor area per building [m²]
1946-1955	01	AB	100	30	56	1680
1956-1970	02	AB	100	30	53	1590
1971-1980	03	AB	100	30	61	1830
1971-1980	03	SFH	3000	1	144	144
1981-1990	04	AB	100	30	64	1920
1991-2000	05	AB	100	30	58	1740
2001-2010	06	AB	100	30	60	1800
2011-2020	07	AB	100	30	68	2040
2021-2070	08	AB	250	30	68	2040

The stock is distributed into two floor area types as shown in Table 4 and two floor area classes with corresponding renovation normal distribution parameters as given Table 5.

Table 4: Distribution of floor area types to floor area classes in the hypothetical case.

Floor area type		
Floor area type ID	Floor area type name	Belongs to Class?
<i>[#]</i>	<i>[string]</i>	<i>[string]</i>
1	Single Family House	Detached dwellings
2	Multi Family House	Compact dwellings

Table 5: Specification of the floor area classes applied in the hypothetical case.

Floor area class				Renovation, distribution parameters	
				Normal dist.	
Class ID	Class name	Number of subvariants given	Residential or service Class?	Mu	Sigma
<i>[#]</i>	<i>[string]</i>	<i>[#]</i>	<i>{Residential, Service}</i>	<i>[#]</i>	<i>[#]</i>
1	Detached dwellings	1	Residential	40	10
2	Compact dwellings	1	Residential	40	10

Three renovation states describing the energy standard of buildings are assumed per cohort. It has been assumed that all buildings are in state 1 at initial time. The combinations of cohorts, renovation states and floor area classes give 27 archetypes. Energy-efficiency measures are only accounted for during major renovations, and hence all archetypes consist of only one variant.

Demolition is simulated for the hypothetical case using Weibull distributions with the parameters given in Table 6.

Table 6: Input Weibull distribution parameters for the hypothetical case.

Distribution	Weibull			
	Average lifetime	Period of years without demolition	Scale parameter a	Shape parameter b
	<i>[year]</i>	<i>[year]</i>	<i>[#]</i>	<i>[#]</i>
Residential buildings	125	40	90	1.2
Service buildings	125	40	90	1.2

Two scenarios are defined for renovation activity in the hypothetical case. For the baseline scenario, it is assumed that all buildings in renovation state 1 going through deep renovation are moved from state 1 to state 2. For the advanced renovation scenario, it is assumed that there is a 50% probability that a building in state 1 going through renovation activity will reach a higher energy standard and be moved straight to the more advanced renovation state 3.

2.4.2 Energy input

Rønneseth (2018) simulated energy intensity profiles in IDA ICE for all apartment block (AB) cohorts 01-07 according to the original state and standard renovation and for Single Family Houses (SFH) from cohort 03 according to the original state, standard renovation and advanced renovation. The resulting hourly delivered energy profiles for different energy carriers are used as input to the model. Furthermore, it is assumed that advanced renovation for all AB cohorts correspond to the original state of AB07. A summary of total yearly delivered energy use for the different archetypes is given in Table 7. An example of an hourly delivered energy intensity profile for district heating is given in Figure 8.

Table 7: Energy use per square meter per year of the different archetypes.

Archetype	Construction period [years]	Initial [kWh/m²]	Standard renovation [kWh/m²]	Advanced renovation [kWh/m²]
AB_01	1946-1955	224	156	64
AB_02	1956-1970	153	140	64
AB_03	1971-1980	136	117	64
AB_04	1981-1990	122	117	64
AB_05	1991-2000	131	115	64
AB_06	2001-2010	87	75	64
AB_07	2011-2020	64	64	64
AB_08	2020-2070	64	64	64
SFH_03	1971-1980	195	150	77

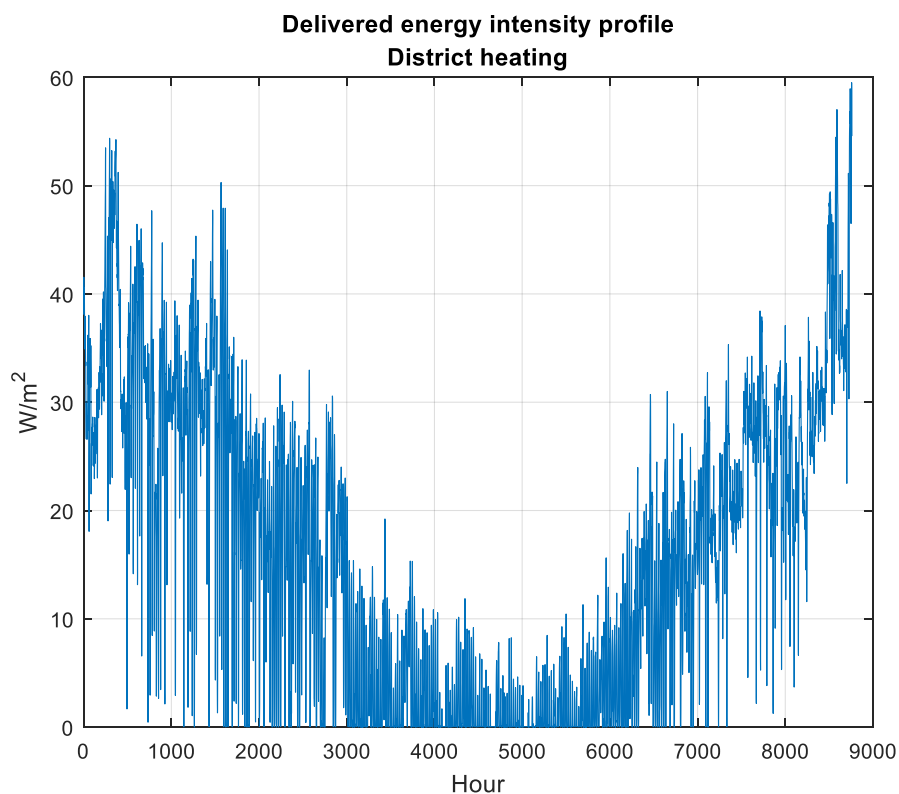


Figure 8: Example of a delivered energy intensity profile used as input for an archetype. In this case, for the archetype apartment block of cohort 1 and state 1 (Rønneseth, 2018).

Load duration curves for the given energy carrier are created by sorting the hourly values from high to low. A load duration curve is a graph showing demand frequency distribution. Load duration curves express the relationship between time and demand by showing the amount of time the demand is greater or equal to a certain level (Poulin et al., 2008). The calculated load duration curve for the example of district heating for AB cohort 1 and state 1 given is given in Figure 9.

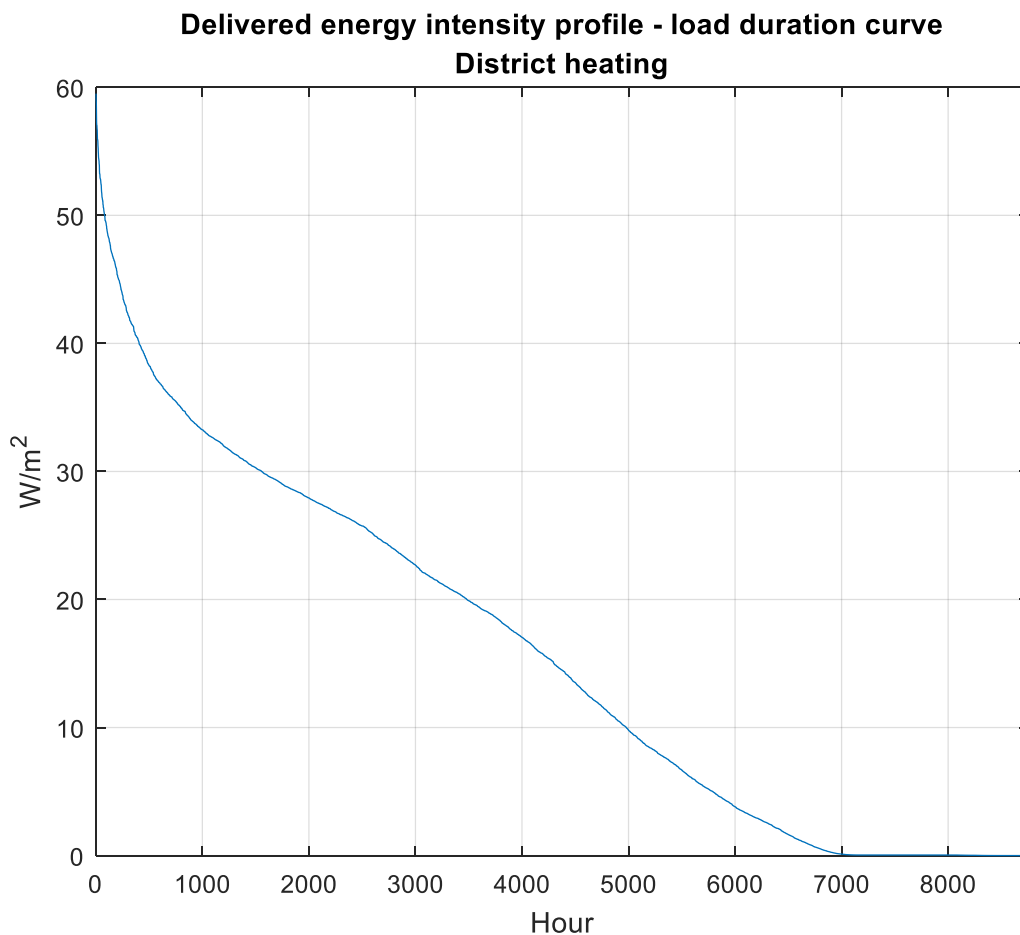


Figure 9 Example of a load duration curve for a given delivered energy intensity profile used as input for an archetype. In this case, for archetype apartment block of cohort 1 and state 1.

2.5 Case description: Gløshaugen campus

Additionally, as a second case study, the neighbourhood Gløshaugen campus is modelled to show how the model can be used to model systems with complex buildings consisting of several floor area types with different functionality. This means that the energy use is highly dependent on the building specific characteristics.

2.5.1 Stock input

Data for the current stock composition at Gløshaugen is given by Woszczek (2017). 17 different floor area types have been identified and are distributed to 5 floor area classes. The initial stock input for Gløshaugen is given in Table 8, and the assumed future construction activity input is given in Table 9.

Table 10: Definition of cohorts for the Gløshaugen case.

Cohorts		
Cohort ID	From Year	To Year
[#]	[year]	[year]
1	0	1950
2	1951	1970
3	1971	1999
4	2000	2016
5	2017	2070

Table 11: Overview of floor area types input and which classes the given floor area types has been assigned to.

Floor area type name	Belongs to Class
[string]	[string]
Kontorarealer (Office area)	Office area
Undervisningsrom (Lecture rooms)	Lecture rooms
Laboratoriearealer (Laboratories)	Laboratories
Studentarbeidsplasser (Student work area)	Student work area
Bibliotek (Libraries)	Student work area
Forretningsarealer (Business areas)	Other
Kantinearealer (Canteen area)	Other
Utstillingsarealer (Exhibition area)	Other
Verksted (Workshop)	Technical rooms
Idrettsrom (Sports area)	Other
Sykehusrom (Hospital area)	Other
Tekniske rom (Technical rooms)	Technical rooms
Vask- og sanitærrom (Closets)	Other
Trafikkareal (Traffic area)	Traffic area
Lager (Storage)	Technical rooms
Tilfluktsrom (Shelters)	Technical rooms
Diverse (Other)	Other

2.5.2 Energy input

Nesgård & Ngo (2017) created a model in IDA ICE of an average campus building represented by the five floor area classes “Lecture rooms”, “Office area”, “Laboratories”, “Student work area” and “Traffic area” (hallways/traffic area). From this model, hourly delivered energy profiles are obtained and delivered energy intensity profiles for each floor area class are estimated. This is used to model the delivered energy for the whole campus based on the current average energy use for the different buildings. Energy profiles for “Traffic area” is used for energy estimations of the floor area classes “Technical rooms” and “Other”.

2.6 Carbon intensities input

Carbon intensities with monthly profiles are given in Table 13 for both district heating and grid electricity. District heating carbon intensities are representative for the city of Trondheim. The shares of different energy sources applied in the district heating production are based on statistics from the local district heating company for 2016 (Solli, 2018; Statkraft, 2017). The carbon intensity of each energy source is taken from various sources as given in Table 12. The fuel mix of district heating in Trondheim is dominated by municipal waste (about 80%). Carbon emissions from municipal waste incineration is assumed allocated to building energy use. It is an ongoing discussion whether it should be allocated to the energy use or to the waste treatment process. Standard Norge (2017) propose an allocation of carbon emissions to waste treatment. An allocation to waste treatment would mean that the estimated carbon intensity of district heating would drop significantly, as the carbon intensity of municipal waste would be set to zero for district heating purposes. Monthly grid electricity carbon intensities are from Vestrum et al. (2018) as given in Table 13. For heat pumps used in district heating, a COP factor of 3 is assumed.

Table 12: Carbon intensities for various heat sources used in district heating.

Energy source	Carbon Intensity [g CO ₂ eq/kWh]	Reference
Municipal waste incineration	216	Lausselet et al. (2016)
Natural gas	261	Ecoinvent Centre (2015)
Biofuel	50	Raadal (2015)
Oil	572	Ecoinvent Centre (2015)
Biogas	27	Lien (2013)

Table 13: Carbon intensities for grid electricity and district heating used for the hypothetical case (Ecoinvent Centre, 2015; Lausselet et al., 2016; Lien, 2013; Raadal, 2015; Vestrum et al., 2018).

Month	Carbon intensity, grid electricity [g CO ₂ -eq/kWh]	Carbon intensity, district heating [g CO ₂ -eq/kWh]
January	37.8	199
February	37.8	190
March	39.0	192
April	41.2	216
May	36.0	213
June	32.6	210
July	33.4	210
August	34.6	209
September	32.6	209
October	35.9	214
November	36.4	221
December	39.3	210

The assumed carbon intensities for grid electricity from Vestrum et al. (2018) are based on a four-year average period (2012-2015) for the given month. Emissions from transmission and power loss for electricity are included, and the carbon intensities represent a production mix adjusted for imports and exports.

For the case study of Gløshaugen, carbon emission intensities for district heating are used for the energy use purposes “district heating” and “heating, local”.

3. Results

The model is run for the hypothetical case and Gløshaugen campus, with the input data and assumptions presented in Chapters 2.4 and 2.5 respectively. Input carbon intensities used in the analysis are presented in Chapter 2.6. The results from the analysis of the hypothetical case are presented in Chapter 3.1, and the results from the modelling of Gløshaugen are presented in Chapter 3.2.

3.1 Hypothetical case

The hypothetical case is modelled to demonstrate the models ability to use well-defined assumptions on renovation activity to move buildings and floor area between archetypes. In this way, the best available assumptions can be used directly to investigate how changes in energy characteristics and emissions from a neighbourhood can be modelled dynamically in the long-term.

3.1.1 Stock model results

Figure 10 shows the simulated future development of the neighbourhood stock towards 2070. The total simulated heated floor area is distributed to floor area types in Figure 10a, and to floor area classes in Figure 10b. Note that in this case the stock input is only given for two floor area types, and each of them is distributed to a separate floor area class. Therefore, Figure 10a and Figure 10b are identical. Furthermore, all new construction is multi family houses (MFH), and therefore the share of the floor area being single family houses (SFH) and detached dwellings is decreasing as some of these are demolished, while the share of MFH and compact dwellings is increasing over time.

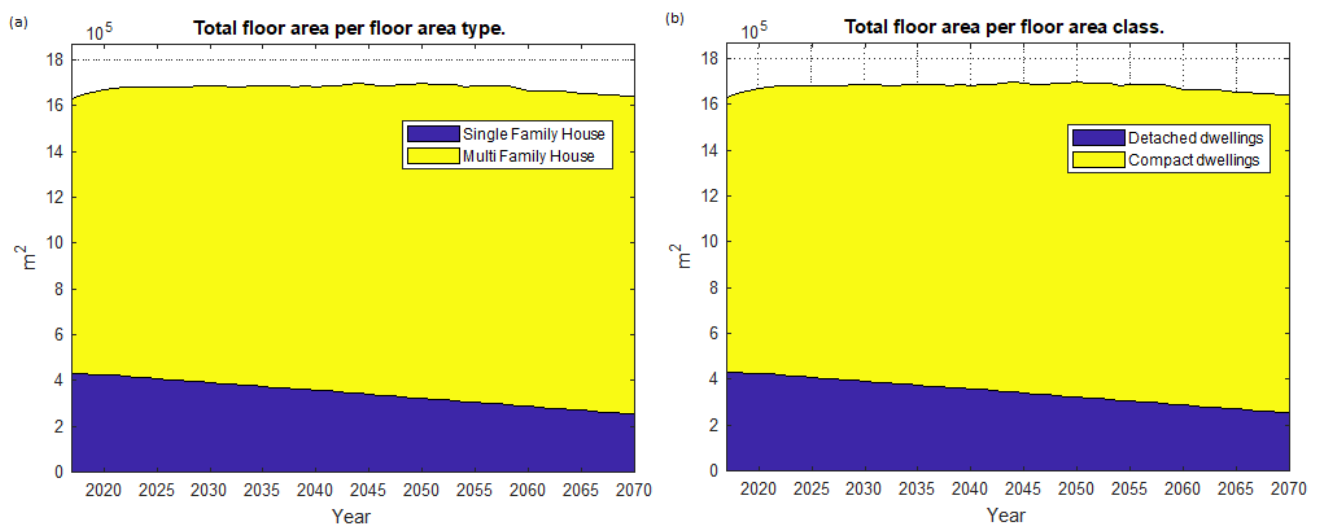


Figure 10: Estimated heated floor area per floor area type for the hypothetical case (a) and per floor area class (b).

Figure 11 shows how the distribution of the stock to various cohorts develops over time. At the initial time of the analysis, in 2017, almost 1 000 000 m² of heated floor area belongs to cohorts C0-C3 and are hence constructed before 1980. In 2070 the simulated heated floor area in these has decreased and is estimated to slightly above 500 000 m². At the same time, it can be seen that the cohorts C7 and C8 have increased over time. This shows that the model estimates that many of the older buildings will be

demolished as they reach their end of life during the period, and how they are replaced by new construction.

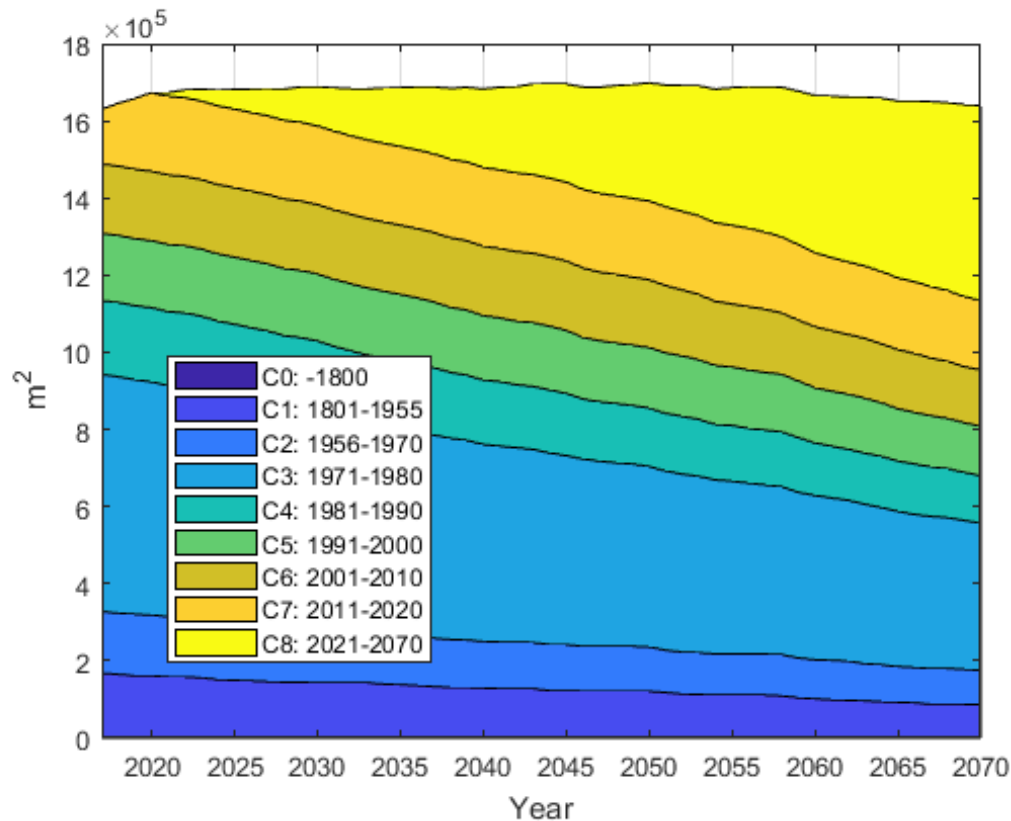


Figure 11: Estimated heated floor area per cohort for the hypothetical case.

Figure 12 shows how the simulated future stock is distributed to the three renovation states, according to the baseline scenario. In 2017, it is assumed that the whole stock is in state 1. Over time the share in state 1 decreases and the shares in state 2 and later state 3 increase. This is due to buildings going through the 40-year renovation cycle described by the distribution input parameters. The corresponding development in shares being in various renovation states according to the advanced renovation scenario is given in Figure 13. In this scenario, the estimated heated floor area in state 3 grows faster as it is assumed that a share of buildings in state 1 being renovated will reach a higher energy standard and move straight to state 3.

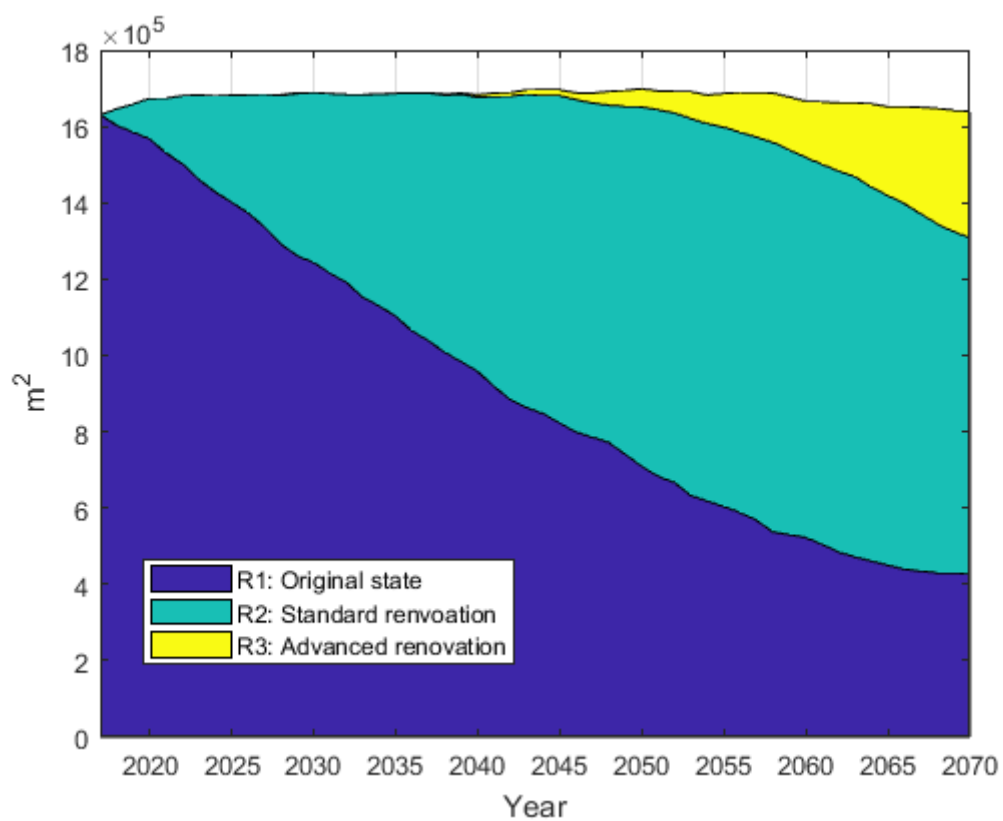


Figure 12: Estimated heated floor area per renovation state for the hypothetical case baseline scenario.

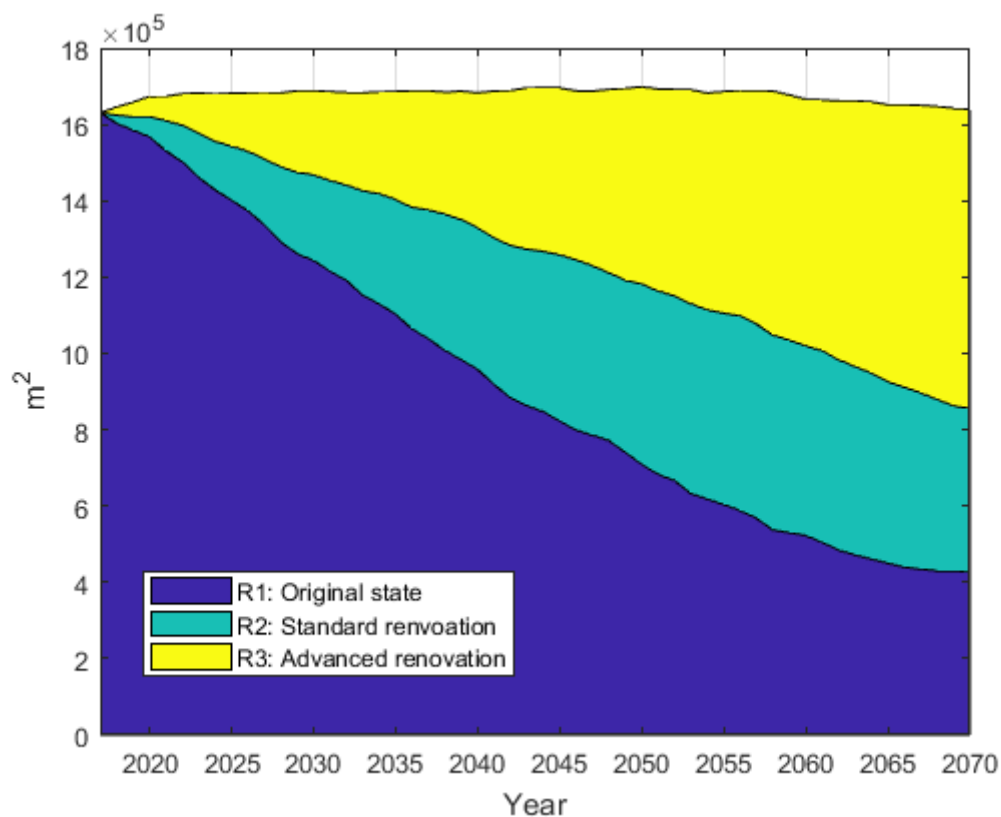


Figure 13: Estimated heated floor area per renovation state for the hypothetical case advanced renovation scenario.

3.1.2 Energy model results

The yearly estimated total delivered energy from all carriers for the system is shown in Figure 14. The estimated delivered energy is estimated to decrease from about 250 GWh at present to about 150 GWh in 2070 for the baseline scenario. For the advanced renovation scenario, a decrease to about 140 GWh in 2070 is estimated.

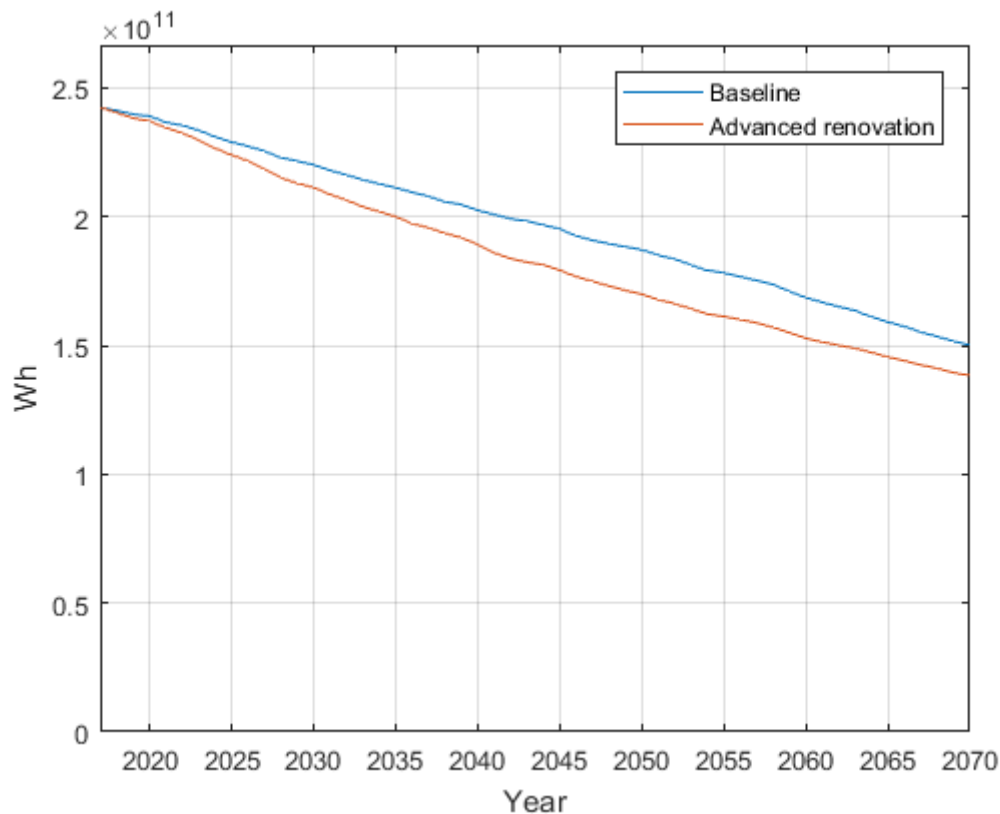


Figure 14: Estimated total delivered energy for the hypothetical case baseline and advanced renovation scenarios.

Figure 15 shows the corresponding development in delivered energy intensity. The average delivered energy per square meter is estimated to decrease from about 150 kWh/m² at present day to about 90 kWh/m² in 2070 for the baseline scenario. For the advanced renovation scenario, a decrease to about 85 kWh/m² is estimated. However, the difference between the energy intensities for the two scenarios are larger in 2050 than in 2070.

Figure 16 shows the estimated delivered energy per cohort the baseline (a) and the advanced renovation scenario (b). The largest decrease in delivered energy is observed in the older cohorts constructed before 1980. For instance, the delivered energy to buildings constructed during 1970-1980 (cohort 3) is estimated to decrease from about 110 GWh/year at present to about 70 GWh in 2050 and 51 GWh in 2070, according to the baseline scenario. For the advanced renovation scenario it is estimated a decrease to about 67 GWh/year in 2050 and about 49 GWh/year in 2070. The difference in yearly delivered energy for the two scenarios are estimated to be larger in 2050 than in 2070.

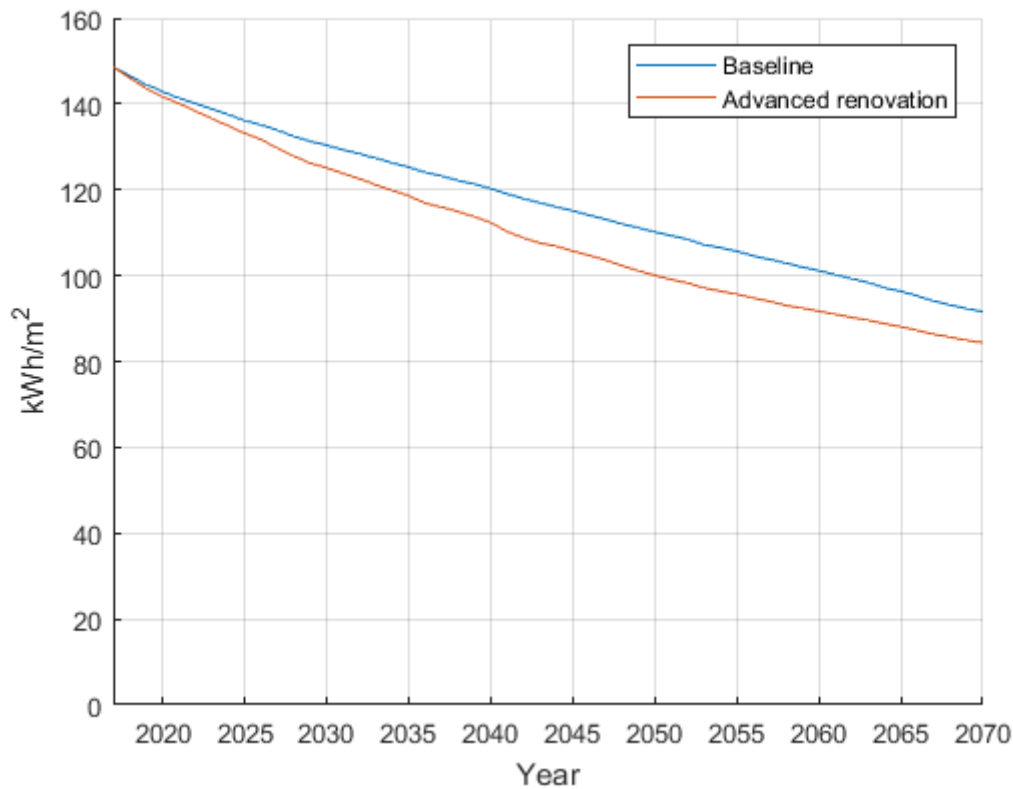


Figure 15: Estimated total delivered energy intensity for the hypothetical case baseline and advanced renovation scenario.

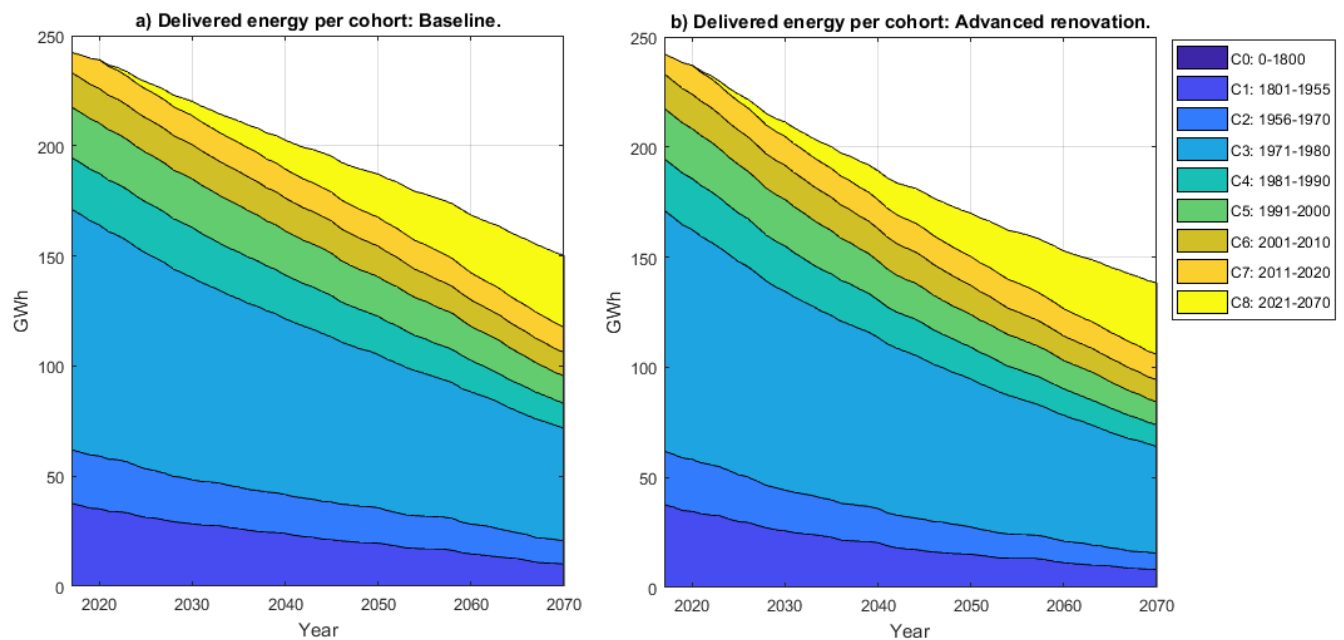


Figure 16: Estimated delivered energy per cohort for the baseline scenario (a) and the advanced renovation scenario (b).

The yearly estimated delivered energy intensity per cohort is given for the baseline scenario in Figure 17a and for the advanced scenario in Figure 17b. The average delivered energy per square meter is

estimated to decrease over time for existing buildings (cohorts 0-6) in both scenarios. The decrease is largest for the oldest cohorts. For instance, the average energy intensity for buildings constructed between 1801 and 1955 (cohort 1) is estimated to decrease from about 225 kWh/m² at present to about 125 kWh/m² in 2070 for the baseline scenario. For the advanced renovation scenario, the estimated delivered energy intensity is about 100 kWh/m² in 2070. Interestingly, the delivered energy intensity of buildings constructed between 1971-1980 (cohort 3) decreases slower than cohort 1 and is estimated to be passed by cohort 1 around year 2040. This is because in the hypothetical case a large number of SFH buildings were assumed constructed in the 70s while the other cohorts consist of solely MFH buildings.

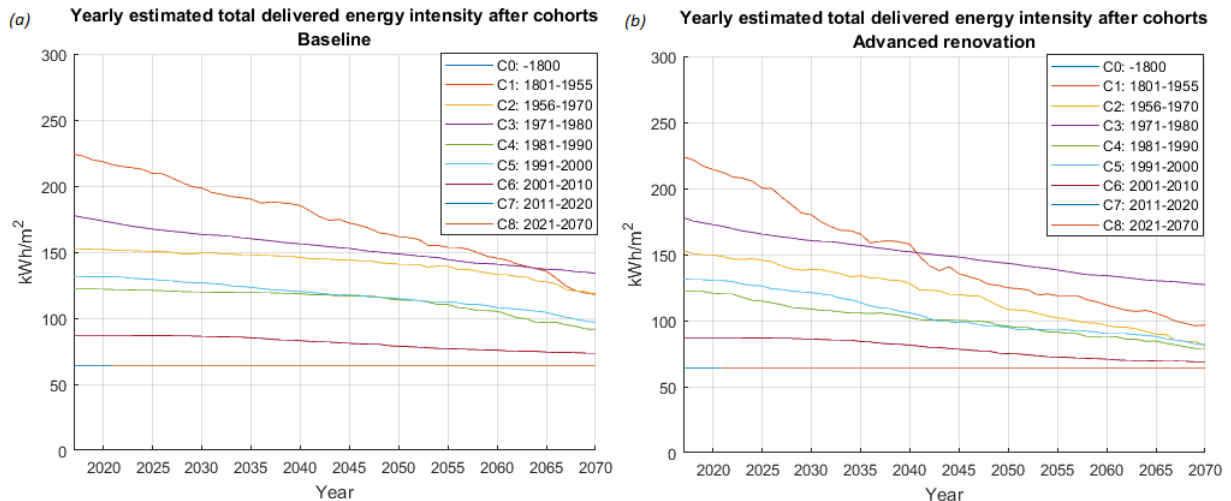


Figure 17: Estimated delivered energy intensities per cohort for the baseline scenario (a) and the advanced renovation scenario (b).

Figure 18 shows the simulated use of various energy carriers. The same energy mix has been used as input for both the baseline scenario in Figure 18a and the advanced renovation case in Figure 18b. District heating is the dominant carrier. The main difference between the scenarios is that the energy use for all carriers are slightly lower in the advanced renovation scenario than for the baseline scenario.

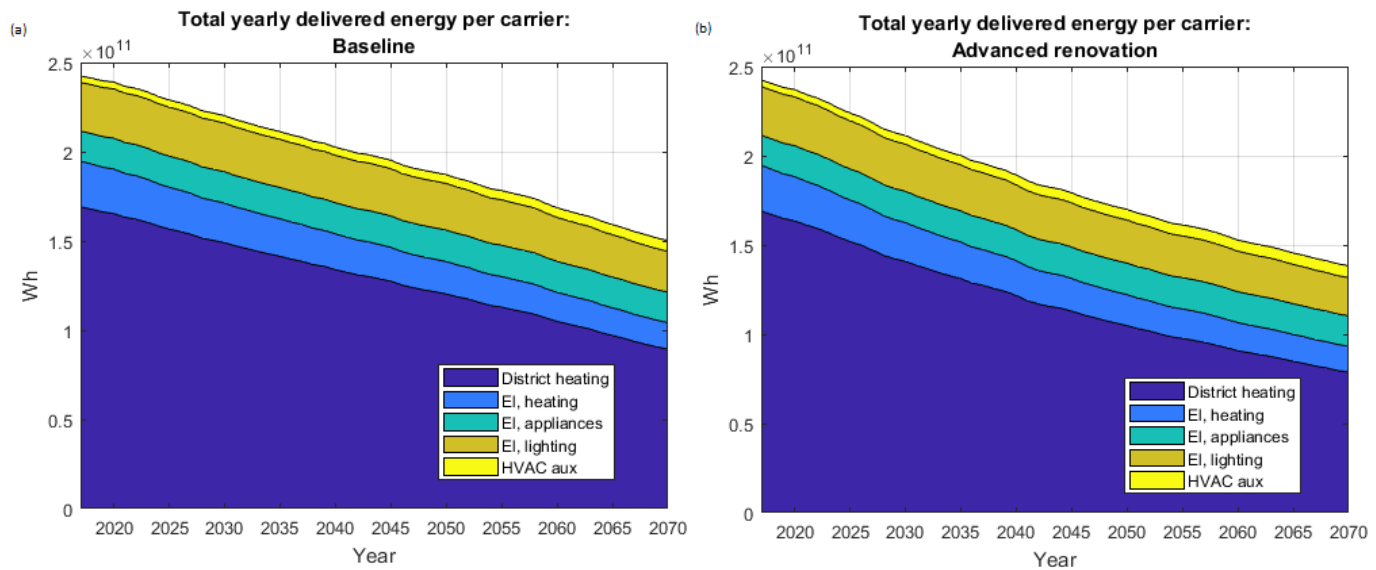


Figure 18: Estimated yearly delivered energy per energy carrier for the baseline scenario (a) and the advanced renovation scenario (b). Electricity is split into four different purposes; heating, appliances, lighting and ventilation (HVAC).

3.1.3 GHG emissions model results

The simulated total GHG emissions from energy use in the system are presented in Figure 19 for both scenarios. The baseline scenario results in a decrease in emissions of around 46 %, from about 37 kton CO₂-eq/year at present day to about 20 kton CO₂-eq/year in 2070. For the advanced renovation scenario, a decrease of around 52% to about 18 kton CO₂-eq/year in 2070 is estimated. Notably, the difference between the scenarios is larger in 2050 than in 2070. This is mainly driven by the fact that about a fifth of the buildings in the baseline scenario is renovated to state 3 between 2050 and 2070. Additionally, demolition of older buildings on the one hand and construction of newer buildings on the other hand make the relative importance of the older cohorts decrease and the newer cohorts increase as shown in Figure 11. This leads to an additional improvement in the future overall energy performance of the building stock.

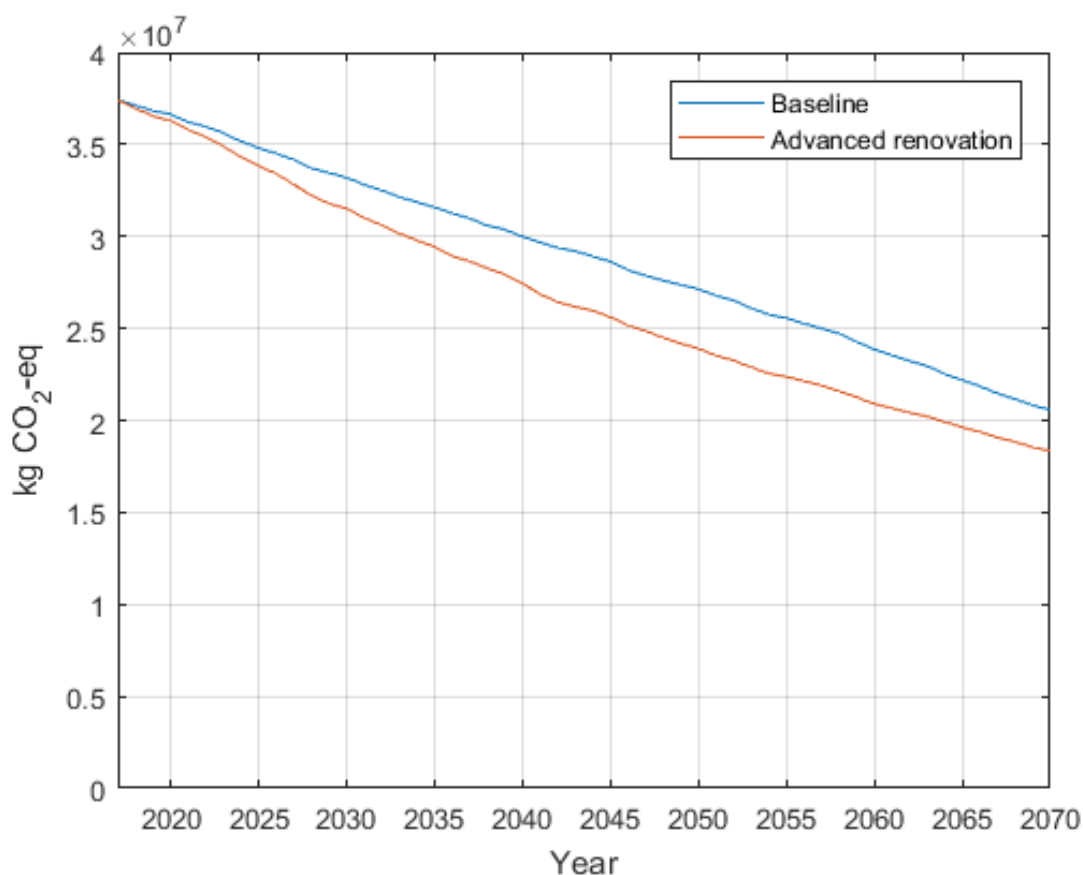


Figure 19: Estimated climate change impact (GWP100) per year for the hypothetical case baseline and advanced renovation scenarios.

Figure 20 shows how the various energy carriers contributes to the simulated total emissions in the baseline scenario (a) and the advanced renovation scenario (b). As the input energy-mix is the same in both cases, the main difference in the results between the scenarios are slightly smaller emissions for all carriers over time for the advanced renovation scenario compared to the baseline. This is due to lower estimated delivered energy because of more ambitious renovation in the advanced renovation scenario compared to the baseline.

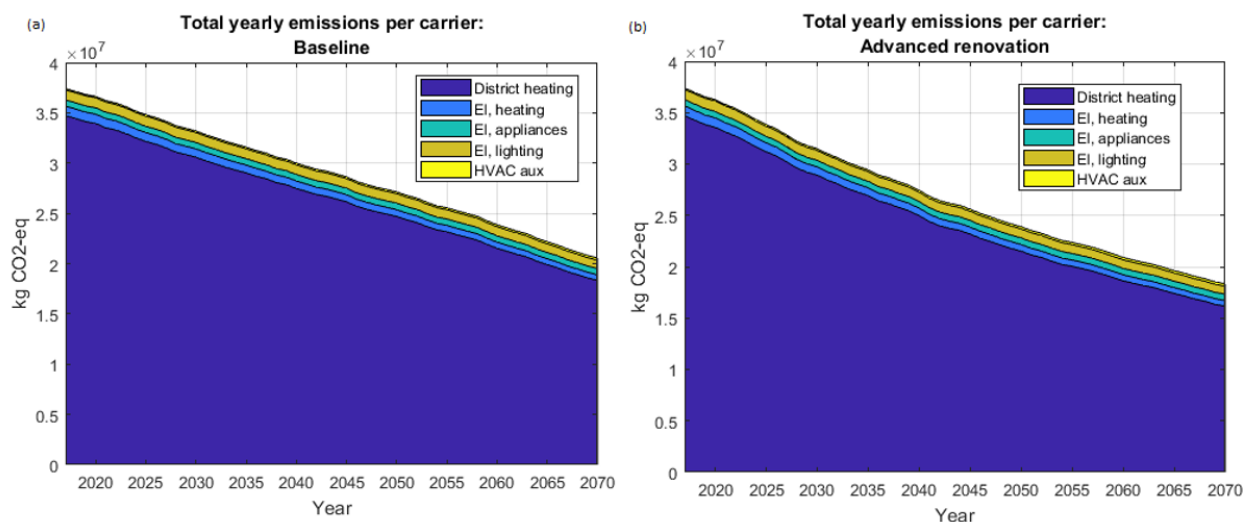


Figure 20: Estimated yearly emissions per energy carrier for the baseline scenario (a) and the advanced renovation scenario (b). Electricity has been split into four different purposes; heating, appliances, lighting and ventilation (HVAC).

A summary of yearly and aggregated GHG emissions for both scenarios in the years 2017, 2050 and 2070 is given in Table 14. A decrease in yearly emissions is observed for both scenarios. Interestingly, the relative difference in reduced annual GHG emissions in the hypothetical neighbourhood when applying the advanced renovation scenario peaks in 2050 and decrease slightly towards 2070. This is due to buildings in the baseline scenario starting to reach renovation state 3 and the increasing relative importance of newer cohorts.

Table 14: A summary of yearly and aggregated GHG emissions for given years (2017, 2050 and 2070) for the different scenarios analysed in the hypothetical case.

Scenario	2017		2050		2070	
	GHG emissions in given year [ton CO ₂ -eq]	GHG emissions aggregated since 2017 [ton CO ₂ -eq]	GHG emissions in given year [ton CO ₂ -eq]	GHG emissions aggregated since 2017 [ton CO ₂ -eq]	GHG emissions in given year [ton CO ₂ -eq]	GHG emissions aggregated since 2017 [ton CO ₂ -eq]
Baseline	37 400	37 400	27 100	1 093 000	20 600	1 567 000
Advanced renovation	37 400	37 400	23 900 (-12%)	1 029 000 (-6%)	18 400 (-11%)	1 447 000 (-8%)

3.2 Gløshaugen campus

3.2.1 Stock model results

Figure 21 shows the simulated development of the Gløshaugen campus during the model period 2017-2070. The distribution to floor area types is shown in Figure 21a and to the more aggregated floor area classes in Figure 21b. The simulated total heated floor area of the stock is increasing from about 300 000 m² at present, peaking at 390 000 m² in 2030 before decreasing to about 320 000 m² in 2070. The results

are highly dependent on the assumptions on future construction. The heated floor area is increasing towards 2030 due to the input new construction, which is according to real plans. After 2060, the heated floor area decreases according to the simulated “natural” need for building demolition. However no further construction activity is assumed in this case study, after the construction that is currently planned. In reality, it is likely that there will be additional construction after 2060 to replace the demolished buildings, or that existing buildings would be kept for heritage reasons rather than replaced. A more realistic and detailed case study than the present one would have to include additional assumptions on future construction, to avoid an unrealistic decrease in total stock size.

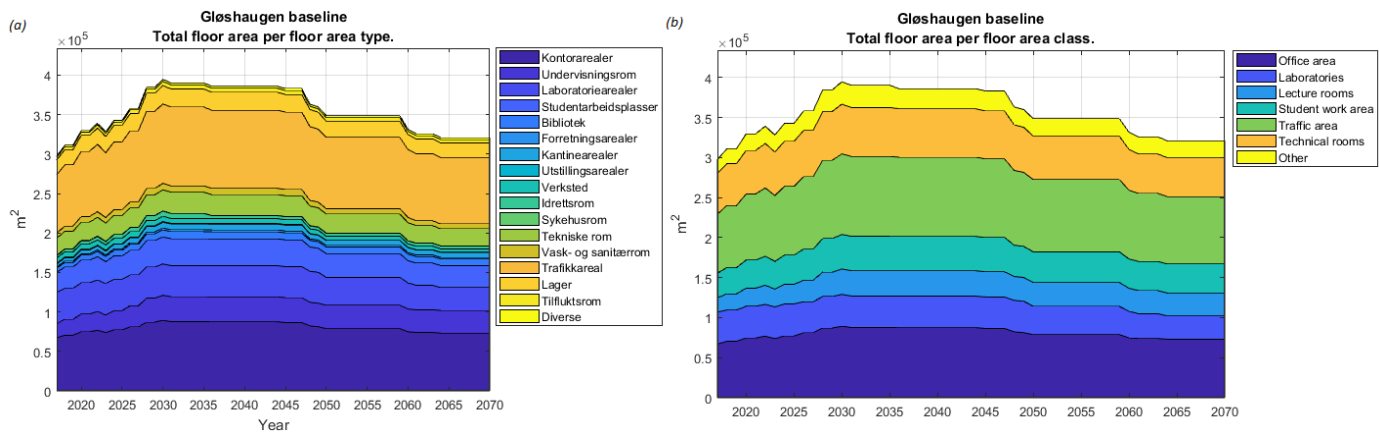


Figure 21: Estimated heated floor area per floor area type (a) and per floor area class (b) for the Gløshaugen case.

Figure 22 shows the heated floor area per renovation state for the period according to the baseline scenario assuming standard renovation. New construction is included in state 1. It can be seen that after the first period with high construction activity, the share being in state 1 decreases, while the share being in state 2 and later state 3 increase. This is due to the simulated renovation activity of buildings going through the respective renovation cycle. Since the Gløshaugen building stock consist of a small number of buildings it is possible to observe the effect of specific large buildings going through renovation activities. Estimated heated floor area per cohort is presented in Figure 23. The floor area constructed before 1950 (cohort 1) is estimated to remain at the current level as the oldest buildings have been given a status as protected buildings. The floor area of buildings constructed during the period 1951-1970 (cohort 2) and 1971-1999 (cohort 3) decreases during the period as some buildings reach their estimated end of life. The heated floor area constructed between 2000 and present day (cohort 4) is estimated to remain stable, while cohort 5 increases according to the assumed new additions to the stock. Cohort 5 consists of new construction after 2017 only.

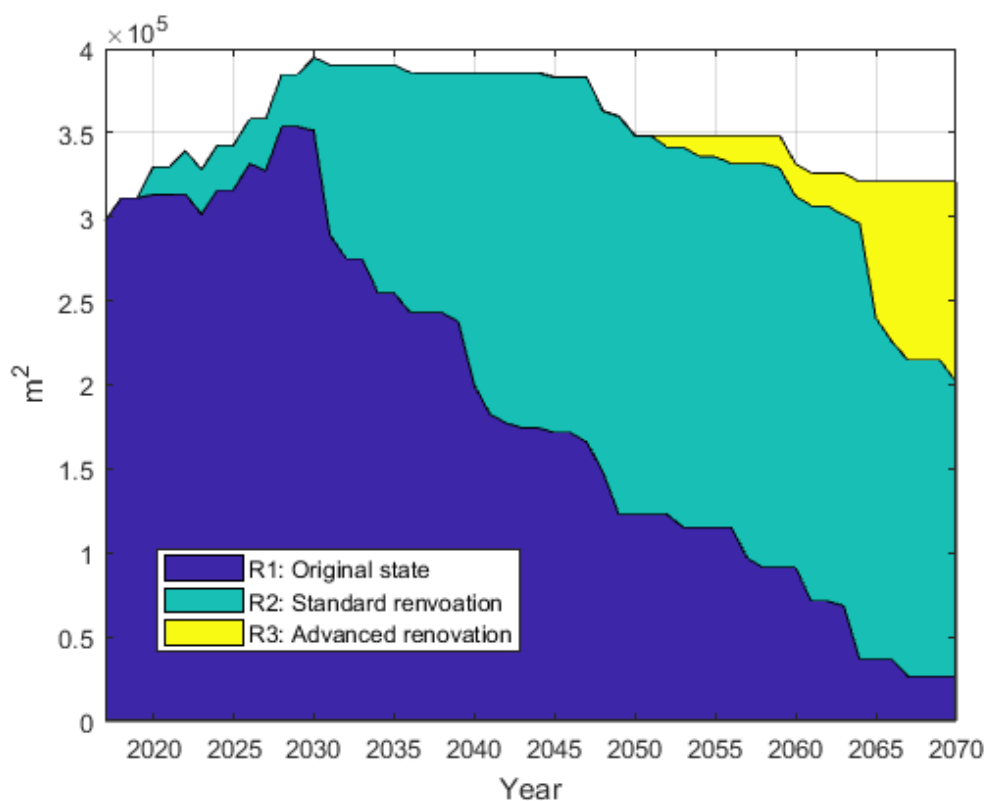


Figure 22: Estimated heated floor area per renovation state for the Gløshaugen case.

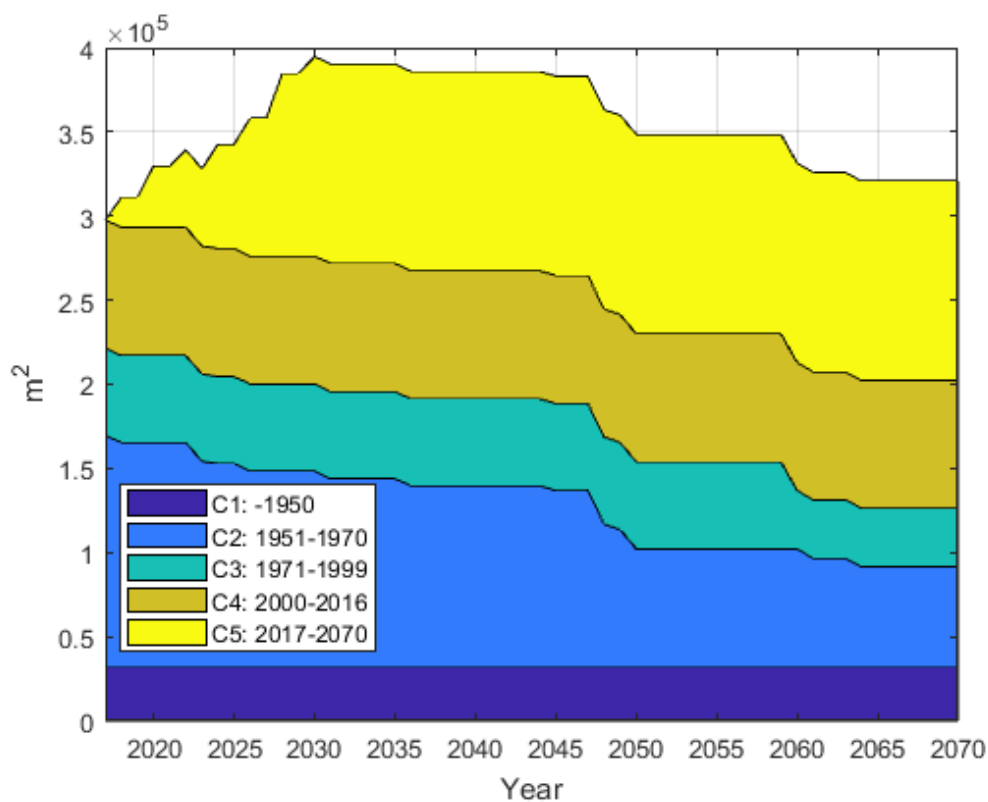


Figure 23: Estimated heated floor area per cohort for Gløshaugen baseline.

3.2.2 Energy model results

The hourly delivered energy to Gløshaugen is estimated per energy carrier for each year. One example of estimated delivered energy from heating in 2017 is shown in Figure 24. Figure 25 shows the load duration curves for the different energy carriers used at Gløshaugen in 2017.

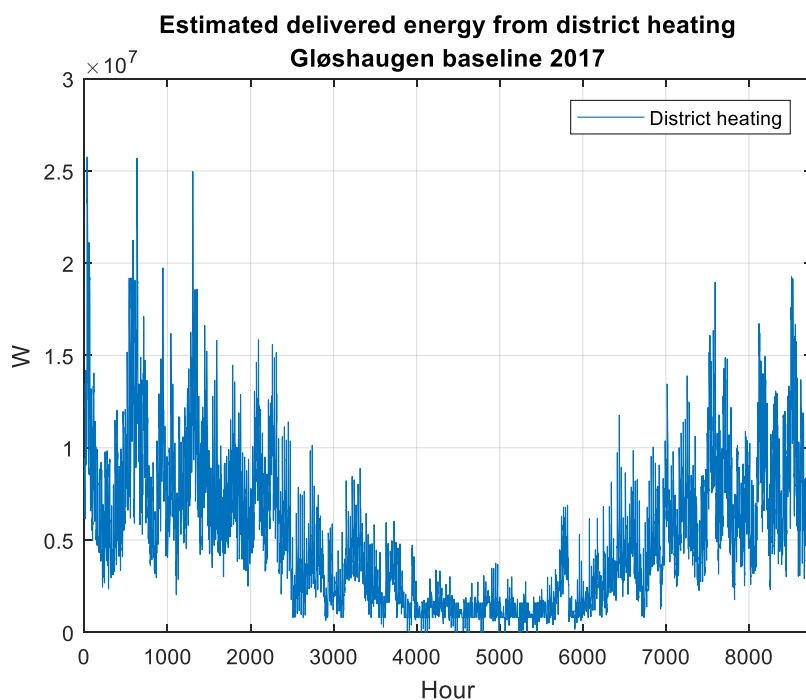


Figure 24: Estimated hourly delivered energy from district heating for the Gløshaugen case baseline scenario in 2017.

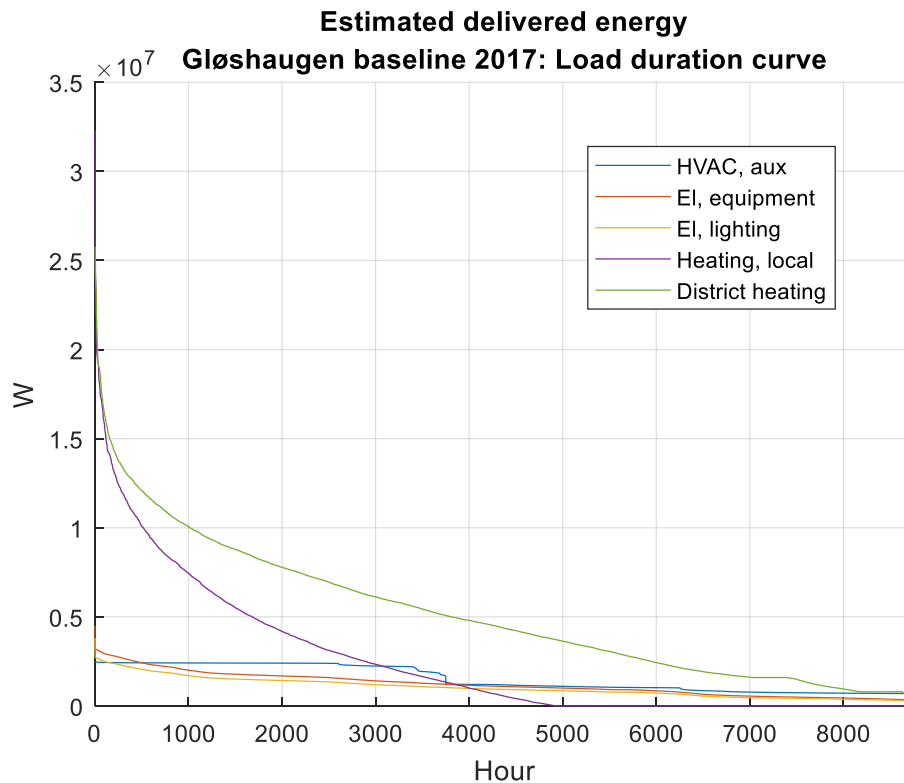


Figure 25: Estimated load duration curves for different energy carriers and purposes for Gløshaugen in 2017.

It is important to consider coincidence when dimensioning the energy supply system of a neighbourhood as it is unlikely that the peak loads of all buildings will happen simultaneously. Here, only a simplified example of such an analysis is presented. In a real case study, the coincidence factor θ would have to be estimated by studying empirical building energy use data. To explore the importance of coincidence, a coincidental analysis is carried out according to the methodology described in appendix A.4. Table 15 shows how the coincidence factors 1, 0.9, 0.8 and 0.7 would affect the estimated hourly peak loads in 2017 in the exemplifying coincidental analysis. “District heating” and “heating, local” are grouped together into one heating category and the others are grouped as electricity. The peak loads of electricity and heating do not occur simultaneously, and therefore the total peak load is not equal to the sum of the two. For Gløshaugen, if the heating demand of all buildings peaks the same hour ($\theta = 1$), it is necessary to dimension for a peak load of 49 MW. However, if peak loads do not happen simultaneously and the actual coincidence factor of the campus is for instance 0.7 it might not be necessary to dimension for a heating peak load that is higher than 34 MW.

Table 15: Coincidental analysis of hourly peak loads for Gløshaugen for total peak load, electricity and heating.

Coincidence factor θ [0-1]	Total [MW]	Electricity [MW]	Heating [MW]
1	53	11	49
0.9	48	10	44
0.8	42	9	39
0.7	37	8	34

The aggregated delivered energy per month in 2017 is presented in Figure 26. The energy use is estimated to be highest in January with about 16 GWh and lowest in July with about 3 GWh. The share of delivered energy given as “Heating, local” is about zero in the summer months. “Heating, local” is modelled as an ideal heater in IDA ICE and has been assumed to be district heating in this analysis.

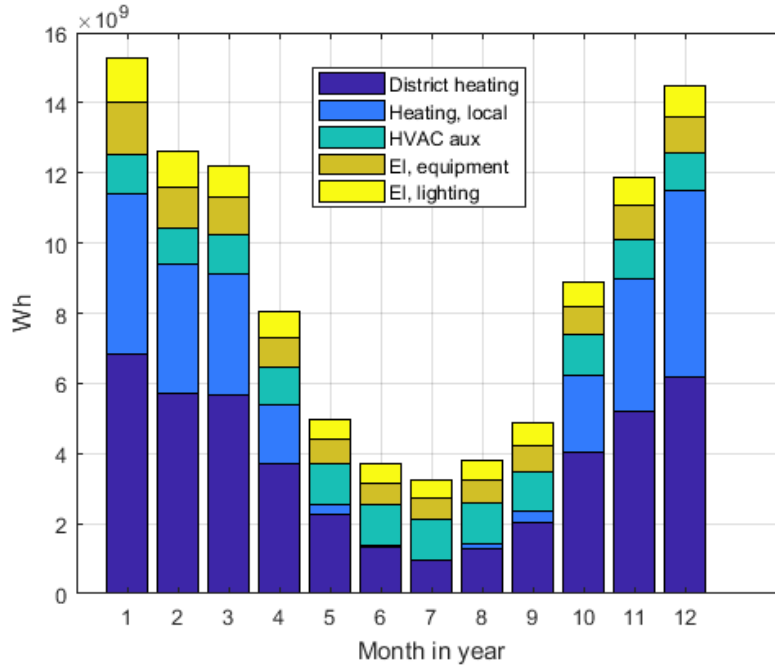


Figure 26: Estimated monthly delivered energy per energy carrier and purpose in 2017 for Gløshaugen.

The simulated future development in aggregated delivered energy to the Gløshaugen stock is presented in Figure 27. Note that due to the use of delivered energy intensity profiles that only varies with floor area class, the estimated yearly delivered energy follows the stock heated floor area development. This is observed by comparing Figure 27 and Figure 21.

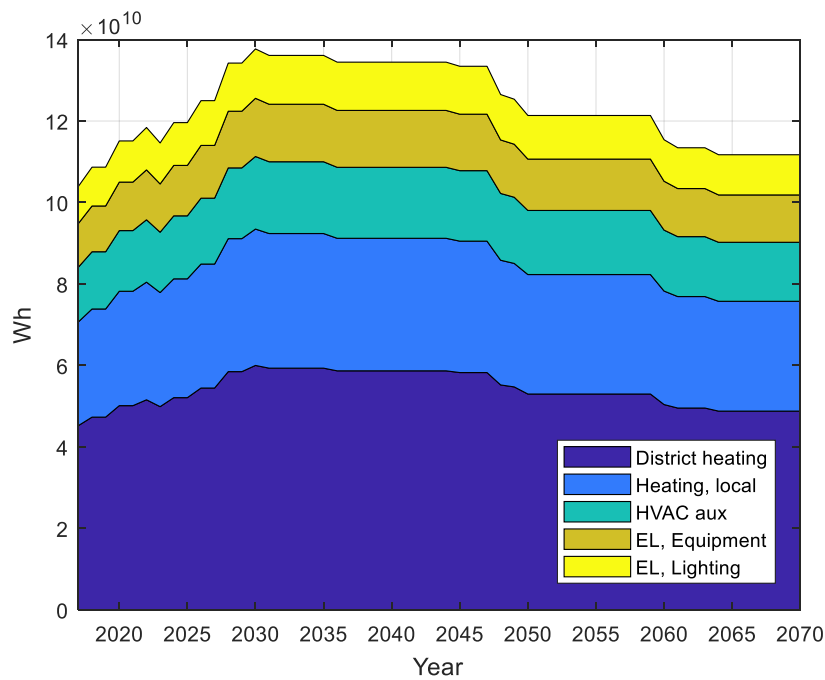


Figure 27: Estimated yearly delivered energy per energy carrier to Gløshaugen.

Estimated yearly delivered energy per cohort is presented in Figure 28a. Comparing this with the development in Figure 21 it seems to follow the same pattern. This is due to the average intensity profiles being used. Figure 28b shows this clearly, as there is no change at all in the estimated delivered energy intensity to Gløshaugen from present day to 2070. The changes in delivered energy to the neighbourhood over time is only affected by changes in stock size according to demolition and construction. In order to estimate changes in delivered energy intensity over time, a variety of different energy intensity profiles is required.

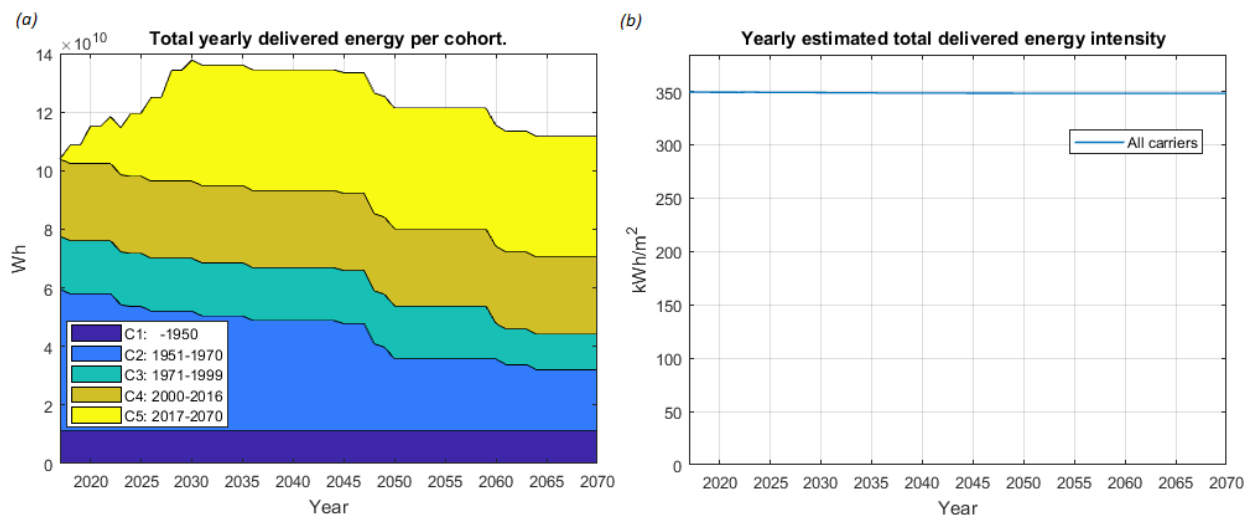


Figure 28: Estimated yearly total delivered energy to Gløshaugen per cohort (a) and estimated total delivered energy intensity to Gløshaugen for all carriers (b).

3.2.3 GHG emissions model result

Estimated GWP100 carbon intensities for district heating and electricity from Table 13 are shown together with the calculated weighted average carbon intensity per month in 2017 in Figure 29. The weighted average is lower during the summer months than during winter months as the heating demand, and hence the use of district heating, is lower.

The carbon intensities applied for “district heating” and “heating, local” are equal to the monthly district heating values given in Table 13. Emission intensity for electricity is applied for the others. Figure 30 shows the estimated aggregated emissions per month for the year 2017, as well as the contributions from the various energy carriers and purposes. GHG-emissions are estimated to be highest during the winter when the heating demand and weighted average carbon intensity peak, while they are lower during summer months when there is less heating demand. Interestingly, the GHG-emissions are higher in December than in January even though the delivered energy in January is estimated as higher than in December. This is due to a higher carbon intensity in the district heating fuel mix in December.

As described in Chapter 2.6, the carbon emissions from municipal waste have been allocated to energy use in buildings in this analysis. It is an ongoing discussion if these emissions should instead be allocated to waste treatment. As the fuel mix used for heat production to district heating in Trondheim is dominated by municipal waste (80%), an allocation of emissions to waste treatment would mean that the district heating carbon intensity would drop significantly. Accordingly, the weighted average would also decrease significantly for all months. This would have to be considered further in a detailed case study of Gløshaugen.

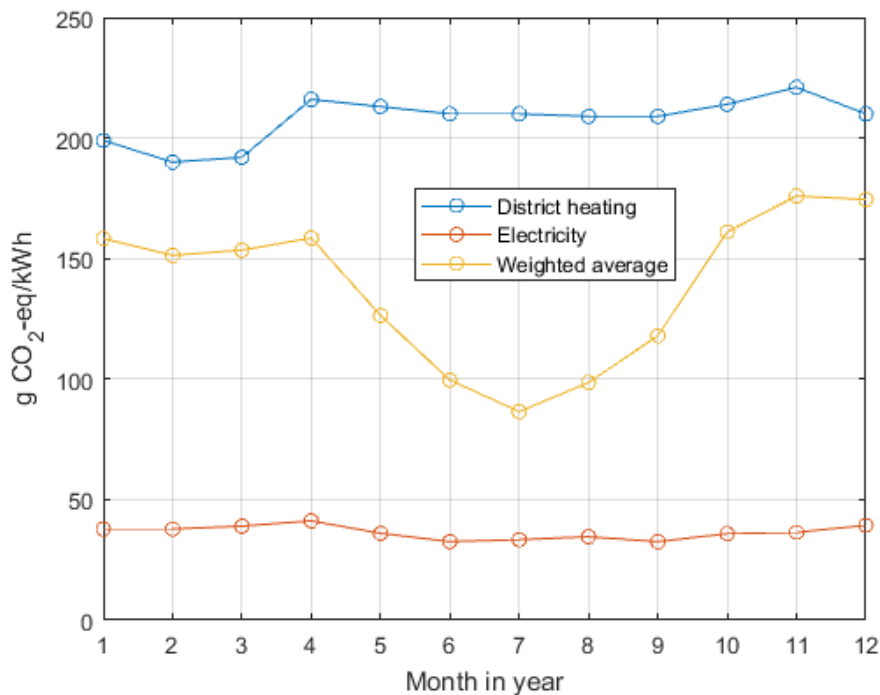


Figure 29: Estimated carbon intensities per month for district heating and electricity, and the calculated weighted average monthly carbon intensity in 2017 for Gløshaugen.

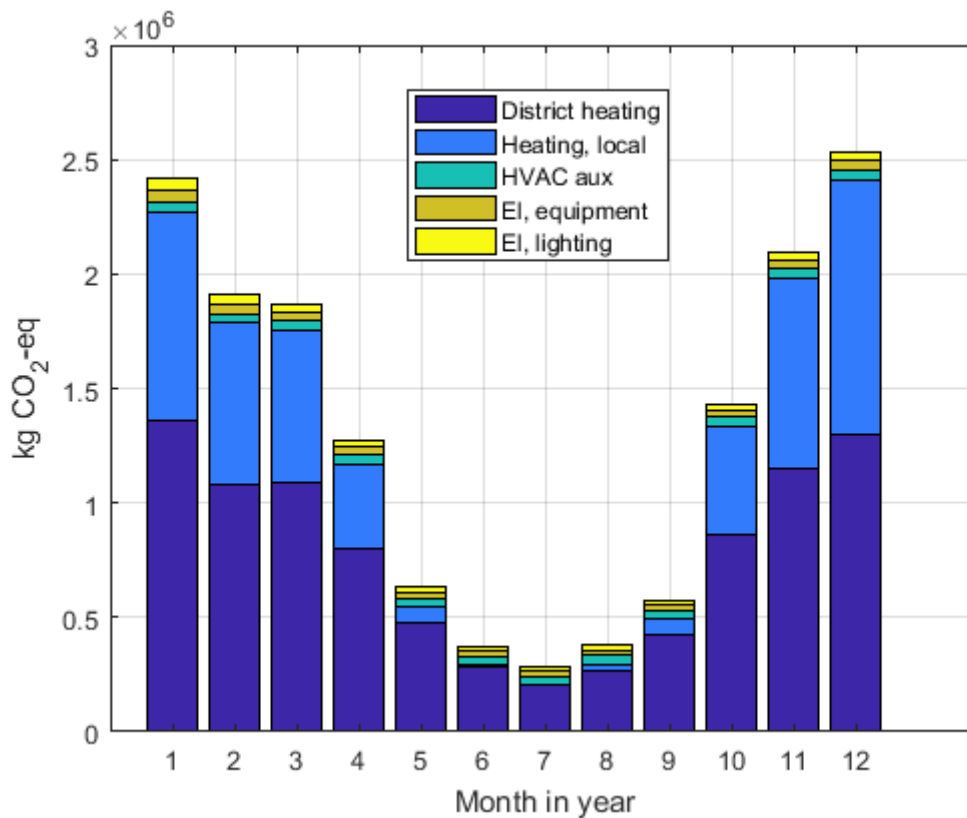


Figure 30: Estimated monthly GHG-emissions in 2017 due to the use of different energy carriers for different purposes for Gløshaugen.

Estimated yearly GHG emissions (GWP100) for different energy carriers related to energy use in the building stock of Gløshaugen are given in Figure 31. The largest part of the GHG emissions during the period is due to heating. The total estimated GHG emissions related to electricity use is estimated as much lower. This makes sense since the carbon intensity of electricity from grid is about 15% of the carbon intensity of district heating. The use of average energy intensity profiles that are constant over time in this case study means that the energy characteristics of the stock only changes with the heated floor area. Therefore, the estimated emissions also follows the same pattern as the estimated floor area for the period. As previously discussed, emissions from municipal waste might instead be allocated to waste treatment and not district heating in a real case study, which would decrease carbon emissions related to heating of buildings significantly.

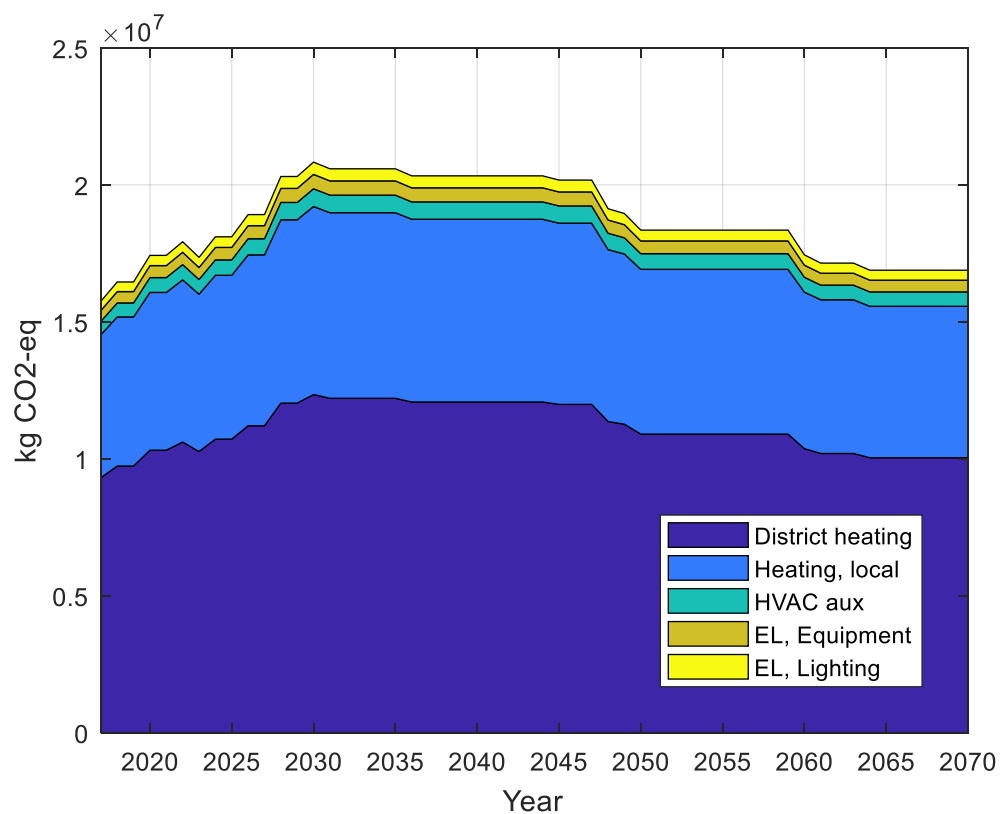


Figure 31: Estimated GWP100 in yearly kg CO₂-eq that are caused by the use of different energy carriers that are given for Gløshaugen.

4. Discussion

4.1 Main findings

Previous work on delivered energy to the dwelling stock on the national level has led to the need for regionalized analysis on the topic. A municipal case study of the city of Trondheim showed that building stocks vary in characteristics also between city districts (Næss, 2017). In order to identify possible future energy pathways and optimal policies it is necessary to analyse even smaller systems such as city districts or neighbourhoods. Therefore, the scenario based dynamic building stock model for energy- and GHG-emission analysis of neighbourhoods was developed.

4.1.1 Building stock analyses

Previous studies such as Næss (2017) and Sandberg et al. (2016, 2017)) have used population and lifestyle parameters to model the development of national and regional building stocks and combined this with segment-specific average values for average floor area and energy intensities. The model presented in this report use detailed building stock information as well as real plans for future activities in the specific neighbourhood.

Results from the hypothetical case consisting of an artificial residential neighbourhood have demonstrated that the model is capable of simulating the dynamics of a neighbourhood stock in a detailed and good manner. In the hypothetical case, future construction plans were assumed to replace buildings that were simulated to be demolished, and hence to keep the total heated floor area in the neighbourhood stable over time. The share of heated floor area belonging to older cohorts decreases over time, while the share being in the future cohort 8 increases. In this way, the dynamics of a neighbourhood stock can be modelled according to real plans or assumptions about future activities. If for instance a neighbourhood with free unbuilt land is analysed, additional future construction of buildings can be assumed. If plans are not available for future renovation or demolition activity, this can be estimated by use of well-defined probability functions.

All the buildings in the hypothetical building stock are assumed to be in renovation state 1 at the initial time. This is an unrealistic assumption as it is likely that parts of the stock will have reached a higher energy efficiency through renovation before 2017 and reached state 2. When applying the model to other case studies, this should be taken into account by starting the modelling period in the past or assuming that a share of the initial stock is already in renovation state 2 in the start year of modelling.

Furthermore, if detailed renovation plans are known for the first few future years, it is possible to specifically input plans for this period before starting the simulation of renovation activities from the end of the planned period. Combining both input plans and simulations for the same year could cause double counting. Estimated results for the advanced renovation scenario in the hypothetical case have demonstrated that the model can be used to analyse different possible renovation ambitions and cycles.

The NTNU campus Gløshaugen has a complex building stock consisting of a large number of different floor area types of different age. The introduction of floor area classes reduced the complexity of the system during modelling, and reduced the number of required input energy profiles accordingly. It has been assumed a future construction of 120 000 m² heated floor area. Currently, construction plans for

96 000 m² heated floor area have been approved, and an additional 45 000 m² is planned renovated (Norwegian Government, 2018). This decision was made after Gløshaugen was analysed as a case study, and therefore, the assumed future construction used as input in this case study does not completely match the actual plans.

By modelling individual buildings as objects, the building stock can be represented with high resolution. The model is able to handle both neighbourhoods consisting of a large number of buildings such as the hypothetical case, and building stocks with complex characteristics such as Gløshaugen campus. The modelled stock activities reflect changes in stock composition that might actually happen in a given neighbourhood over time.

Building stock scenario analyses can be performed for a neighbourhood by changing different input parameters: plans and probability parameters for future construction-, demolition- and renovation activities, renovation state change probability, building protection or class and cohort definitions. This allows for the creation of roadmaps showing possible pathways of future stock development and for analysing the importance of various parameters for the model results. The stock model results should not be regarded as a prediction for how the future stock will actually develop down to each individual building, but rather as an attempt to describe a possible future pathway.

4.1.2 Energy analyses

In the presented energy analysis of neighbourhoods, the long-term development in energy demand is modelled in detail by combining estimated results from a building stock model with hourly delivered energy estimations. Simulated energy intensities or empirical energy data for given buildings in the neighbourhood are used.

Results for the hypothetical case suggest that the total energy use decreases in the future, despite the fact that the total heated floor area stays rather stable. This is due to renovation of buildings in older cohorts and old buildings being replaced by new construction. The energy use is estimated to decrease for all carriers, and the share per carrier of the total is estimated to remain quite stable. This is because no significant shift in the energy mix has been defined in the input. When assuming more buildings to reach better energy standards when going through deep renovation, the results for the advanced renovation scenario shows a potential for reducing energy use in the neighbourhood over time compared to the baseline. In the advanced renovation scenario, there is a probability that buildings in their original state will go through advanced renovation without having gone through a standard renovation first. Interestingly, the annual gains in kWh/m² are better in 2050 than in 2070 when comparing the scenarios. This is due to the assumption that buildings that are already in renovation state 2 will reach state 3 when being renovated the second time. As a larger share of the stock is simulated to have been renovated two times, the average energy use intensity in the baseline scenario starts to catch up with the advanced renovation scenario when approaching 2070. This is observed when comparing the delivered energy intensity per cohort where the intensity for the older cohorts drops much faster the first years in the advanced renovation scenario than in the baseline scenario. Later, after about 2050, there is a faster decrease in energy intensity per cohort in the baseline scenario. If a longer time horizon were to be analysed, the energy use intensity per year would converge towards the same numbers as more buildings are renovated. By aggregating the estimated delivered energy use for a given time horizon, the total gains in reduced energy use can be estimated and compared across scenarios.

For the NTNU campus Gløshaugen, a theoretical hourly heating peak load of 49 MW and an electricity peak load of 11 MW were estimated. It is, however, unlikely that individual building peak loads happen simultaneously. Depending on the tendency of peaks from multiple buildings to occur during the same hours, the actual peak loads can be estimated through coincidental analyses. When aggregating to estimated monthly delivered energy values, large variations are seen between months. This is as expected as the heating demand is much lower during summer than in winter. In addition, the electricity used for lighting and equipment is expected to be lower during the summer as occupancy of both students and employees is lower during holidays. The estimated delivered energy is aggregated further to annual levels from today until 2070. A clear weakness of using the average delivered energy intensity profiles that do not vary between renovation states and cohorts is identified as the energy use follows the development of the heated floor area. The estimated total delivered energy intensity kWh/m² per year is more or less constant. This is very unrealistic as there will be renovation and new construction improving or replacing old buildings during such a long period. Therefore, a larger database of energy intensity profiles is required as input to get a realistic long-term analysis of the energy use in the neighbourhood.

Combining building stock models with energy analyses makes long-term modelling of the energy use in neighbourhoods possible. Scenario analyses are defined by changing different input parameters and can form a basis for detailed analyses of possible future energy pathways, for instance by changing the energy profiles of different archetypes by varying the hourly energy demand or energy mix. Different variants of measures, such as upgraded windows or a change of heating system, can be modelled using energy simulation software such as IDA ICE. By shifting buildings between archetypes and variants over time, the effects of specific possible energy measures on the neighbourhood energy use can be identified and compared across scenarios.

4.1.3 GHG emission analysis

GHG-emissions caused by the operation phase of a Neighbourhood are simulated by use of estimated delivered energy and carbon intensities. The estimated weighted average carbon intensity per time is given as a function of carbon intensities per carrier and the share of carriers in the energy mix per time. GHG-emissions can be estimated for the hourly, monthly and yearly level.

A decrease in annual GHG-emissions by about 46% is estimated in the hypothetical case baseline scenario and 51% decrease for the advanced renovation scenario from present day towards 2070. This correlates with the estimated decrease in energy use. No change in the monthly carbon intensities per energy carrier over time is assumed in these scenarios, so the decrease is due to energy efficiency measures through renovation and the replacement of older buildings with new construction. Similarly, as for the estimated annual delivered energy, the difference between the scenarios is higher in 2050 than in 2070 due to the renovation of buildings from state 2 to 3 happening at the end of the model period in the baseline scenario. The aggregated GHG emissions from 2017 to 2070 is estimated to be 8% lower in the advanced renovation scenario than the baseline scenario. This is an example of how the model can be used to compare two different future scenarios with respect to estimated future GHG emissions. The way annual gains vary over time shows that the chosen time horizon analysed can be of importance to final conclusions.

The estimated monthly weighted average carbon intensity for Gløshaugen in 2017 varies a lot between months. It was highest in November at about 175 g CO₂-eq/kWh and lowest in July with about 85 g

CO₂-eq/kWh. This reflects the changes in the energy mix used in the delivered energy to Gløshaugen over the year. During winter, the heating demand is high and the share of district heating is high. During summer, the heating demand is low and the energy mix is dominated by grid electricity. As shown in Table 13 and Figure 29 the carbon intensities are much higher for district heating than for electricity. The highest aggregated monthly GHG emissions in December are about 9 times higher than the lowest emissions in July. Considering that January has a higher total estimated energy use than December, the estimated higher GHG emissions in December is due to the weighted carbon intensity being higher in December than in January. The estimated annual GHG emissions for Gløshaugen towards 2070 follow the exact same trend as the estimated heated floor area. This is due to average delivered energy intensity profiles being used as input to the model for all cohorts and renovation states combinations. This shows the need for more detailed input data on delivered energy for various construction periods and renovation states, so that an energy saving is seen in the model when a building is renovated or replaced by new construction with improved energy efficiency.

In this analysis, GHG emissions from the combustion of municipal waste used to produce heat for district heating have been allocated to building energy use. It is an ongoing discussion whether these emissions should instead be allocated to the waste treatment process. If allocating the emissions from combustion of waste to the waste treatment process, the carbon intensity from municipal waste to district heating will be zero. In both case studies presented in this report, the energy use is dominated by the need for heating. District heating is the dominant energy carrier in both cases, and the assumed energy carrier mix used for district heating corresponds to the district heating system in Trondheim, with about 80% municipal waste. Hence, the chosen allocation method has a large impact on the model results. In later case studies, the user of the model can decide what allocation method to use.

Scenario analysis can be done by changing the monthly carbon intensities for different energy carriers over time. Estimated GHG-emissions are highly dependent on the stock and energy model results. All parameters that influence the estimated heated floor area and the estimated delivered energy are important for the estimated emissions. Different future pathways of GHG-emissions can be identified by changing input parameters. Policies and measures can be compared and a roadmap can be created to benefit policy-makers or other stakeholders.

4.2 Uncertainties

There is high uncertainty in any building stock energy model, and the uncertainty is larger when estimating further into the future.

When the model is applied to a real, given neighbourhood, there will be uncertainty in various parts of the model. The extent of assumed or simulated future construction, renovation and demolition may not correspond to the real development of the neighbourhood. The assumed lifetime and renovation cycles of the buildings are also highly uncertain, as well as the assumptions on what energy-efficiency measures will be implemented when renovating in future and the assumed energy profile of new construction.

Furthermore, there is uncertainty related to how the model simulates renovation and demolition activity. If the building stock is small, there might not be enough activities to simulate to get a good randomized distribution. When analysing a small stock, it is probably better to manually estimate renovation and demolition years for specific buildings. This is a bigger problem considering the modelling of the

Gløshaugen case than for the hypothetical case presented in this report. In the Gløshaugen case, it is possible to spot in the graphs when the larger buildings are demolished or renovated. These specific activities affects the state of the stock much more than it would if the stock was larger.

Finally, the real energy use of a building might differ substantially from the energy load profiles that are applied. They are based on either empirical data or simulations. The actual energy use of a building might also change over time even though the building is unchanged according to changes in what the building is used for or in user behaviour. There is also uncertainty related to what heating systems that will be used in the buildings in future, as well as the energy mix, emission intensities and changes in outdoor climate.

Hence, when applying this model, it is important to be aware of the underlying uncertainty in the input parameters and model assumptions and to evaluate how they affect the model results. This can be done through uncertainty analyses and/or sensitivity analyses. The underlying uncertainty is not a problem if the possible changes in the inputs do not affect the overall conclusions of the analysis.

4.3 Strengths and limitations

The model is flexible in the way that it can model any building stock by use of existing data. It takes into account the highly complex characteristics and allows simplifications to be made using floor area types and classes. The model allows for a high time resolution and results can be produced on an hourly basis. However, if less detailed data is available, the model can also simulate the monthly or yearly energy use in the neighbourhood. The model is fully transparent, and the importance of the uncertainty in the input variables and assumptions can easily be assessed.

Furthermore, the model is flexible in the way it allows for using any number of user defined energy carriers with individual carbon emission intensities as input. The emission intensities can be given per month or per year. Results are calculated per energy carrier and total. In this way, it is possible to analyse and understand in detail how a change in the energy mix or carbon intensities at a given time will affect the GHG emissions of the system.

The model makes use of energy load profiles, which can be either building specific and based on empirical data, or class specific based on simulations or assumptions. This flexibility is a strength of the model. The requirement of detailed inputs is, however, also a limitation of the model, as energy use profiles might not be available for all the given buildings or floor area classes or for all the relevant renovation states and variants. This was exemplified by the Gløshaugen case study presented in this report.

The model is unnecessarily complex when modelling smaller neighbourhoods with only few different building types or over a brief time period. It is, however, very useful when analysing more complex systems.

4.4 Future work

This work has demonstrated how dynamic building stock modelling can be combined with energy- and emission flow analysis to estimate the energy use and GHG emissions of a neighbourhood. However, there are still several aspects to consider that could further improve the model.

A database of energy intensity profiles for different building archetypes and variants should be developed. These profiles can be created using modelling programs such as IDA ICE. The larger the database, the more accurately it will be possible to model the energy use of a system and the more types of buildings and states or variants can be included in the analysis even if empirical or building-specific data are not available.

The model should be developed further to include the possibilities for energy generation and storage in the individual buildings or on a neighbourhood level, as indicated in Figure 5. Possible available technologies should be identified and a database giving input details about parameters such as storage capacity, generation profiles and carbon intensities should be created.

A preliminary attempt to model Gløshaugen has been done in this work, but further work is needed. At present only delivered energy profiles for five floor area classes modelled as the average Gløshaugen building are available. More energy profiles are required to be able to simulate the future energy demand in the system in a good way. In their master's thesis in the spring of 2018, Nesgård and Ngo will further develop their IDA ICA model to be able to simulate the energy load profiles for a larger number of cohorts, renovation states and variants. Woszczek will explore the possibilities for local energy generation and storage at Gløshaugen in her master's thesis. When these analyses are available, it will be possible to carry out a complete study of the future development in energy demand at Gløshaugen.

Additionally, Dæhlin will analyse the carbon intensities in the different energy carriers used in the energy mix at Gløshaugen. This will allow for better analyses of the current and future GHG-emissions caused by Gløshaugen. Currently, the carbon intensities are given on the monthly or annual level. It is possible to use a more frequent time step if for instance hourly intensities can be obtained. Further considerations on whether to allocate GHG emissions from the combustion of municipal waste to district heating or the waste treatment are needed.

It could be of interest to expand the model by adding estimations of material use in buildings. This could be done in the same way as the energy estimations by using intensity profiles per archetype for material need. Another possibility is to add cost estimations of stock activities, hourly delivered energy or changes in the energy system.

Furthermore, the model should be tested on other ZEN pilots, e.g. Furuset, or other larger neighbourhoods.

5. Conclusions

A dynamic building stock model has been developed for energy- and GHG-emission scenario analyses of neighbourhoods. The model is implemented in Matlab and can take input from standardized Excel spreadsheets. Two case studies have been analysed, a hypothetical case with an artificial residential area as well as the NTNU campus Gløshaugen. The main purpose of the report is not to perform realistic case studies and scenario analyses, but rather to demonstrate how the model can be used to analyse neighbourhood building stocks. Many assumptions have been made on input parameters. To produce a reliable case study, a high quality and well-defined input data and parameters is needed. Such detailed case studies are planned in the further work within the FME ZEN in 2018 and 2019. Still, the presented case studies demonstrate how the model is able to simulate dynamic development of a neighbourhood building stock. The model makes use of real plans or well-defined assumptions on the activities that lead to changes in the stock size, composition and characteristics. The way the changes in energy efficiency is directly linked to these well-defined assumptions on renovation and construction is a strength of the model. Furthermore, the model is flexible in the way it can make use of empirical energy data whenever available, and otherwise, simulated or average data can be used.

Since the model is scenario based, it allows for comparing various possible measures and policies. In this way, roadmaps giving potential energy- and emission pathways can be created and the most important factors for future development can be identified. Hourly peak loads in delivered energy for different energy carriers in a neighbourhood can be estimated. The building owners and users in the neighbourhood can make use of this when planning future development of their building stock. This is highly relevant e.g. for the case of Gløshaugen, where there is only a few, large institutions owning and using the whole building stock in the neighbourhood. Furthermore, policy makers and local authorities can make use of this when creating specific policies for a given area. The simulation of the aggregated energy profiles within a given geographical area is also highly relevant for energy companies. For district heating suppliers, it is important to know the estimated future heating demand and peak loads when considering whether to extend their grid to the area. For electricity suppliers, it is important to know the estimated peak load to dimension grid capacity correctly.

A larger database of different building archetypes is required to be able to model neighbourhoods with various types of buildings being from different construction periods and in different renovation states. The energy use in service buildings depends strongly on the building function. However, for dwellings, the age is very important and intensity profiles for all SFH cohorts are needed to model a neighbourhood with SFHs from different construction periods. Having a large database of archetype delivered energy intensities to draw on is necessary when modelling complex neighbourhoods.

Further work is needed analysing the carbon intensity per time step for different carriers. Specifically, considerations on whether to allocate GHG emissions from the combustion of municipal waste to district heating or to waste treatment is needed when district heating is used for the thermal energy demand. Model users can define the number of energy carriers in a neighbourhood with individual monthly carbon intensities. This is a clear strength of the model as it allows for modelling complex energy infrastructure and systems, but it also allows for grouping energy carriers into only electricity and heating if simplicity is preferred.

A natural next step is to implement neighbourhood generation and storage. Input information about energy generation and storage technologies that can be implemented on the neighbourhood level is needed. A database suitable for scenario analysis should be created.

The presented exemplifying case studies have demonstrated that the model is suited to analyse the long-term development of neighbourhood building stocks. Even though the modelling period can be decades, it still uses frequent time intervals and results are calculated hourly for the whole period. It has the potential to be a tool for policy makers and stakeholders planning future development of neighbourhoods.

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Appendix A: mathematical framework

Appendix A describes the mathematical framework used in the presented model. Equations used in the building stock model is presented in A.1, equations used in the energy model is presented in A.2, equations used for GHG emission analysis is presented in A.3 and equations describing coincidental analyses is presented in A.4.

A.1 Building stock model

All the given buildings in the stock at the start year of the modelling period define the initial state of the stock. Over time, the stock size and composition can change due to construction and demolition as described by Equations 1 and 2.

$$B(t) = B(t - 1) + \frac{d}{dt}B(t) \quad (1)$$

$$B(t) = B(t - 1) - B_{dem}(t) + B_{new}(t) \quad (2)$$

Where:

$B(t)$: Building stock at the end of year t .

$B_{dem}(t)$: Demolition activity in year t .

$B_{new}(t)$: Construction activity in year t .

In addition, the characteristics of the stock can change due to renovation activity B_{ren} ,

Since each building consists of one or more units, the total individual heated floor area A_b for a given building is equal to the sum of the heated floor area of all units belonging to the building A_u , as described in Equation 3. Furthermore, the heated floor area of a given floor area type y in each building b , $A_{b,y}$, is equal to the sum of the floor area of all units belonging to that floor area type in the given building, as described in Equation 4. Finally, each floor area type y belongs to a floor area class z . The heated floor area for a given class per building $A_{b,z}$ is equal to the sum of all floor area types belonging to the floor area class in the given building, as described in Equation 5.

$$A_b = \sum_{u \in b} A_u \quad (3)$$

$$A_{b,y} = \sum_{u \in y} A_{b,u} \quad (4)$$

$$A_{b,z} = \sum_{y \in z} A_{b,y} \quad (5)$$

The building specific heated floor areas are aggregated to the building stock level. The total heated floor area for the system belonging to a specific floor area type A_y is equal to the sum of the floor area of the given floor area type A_y for all buildings in the system, as described in Equation 6. The total heated floor area belonging to a given floor area class A_z is equal to the sum of $A_{b,z}$ of all the buildings in the system. This is also equal to the sum of A_y for all floor area types belonging to the given floor area class, as described in equation 7. The total heated floor area in the building stock A_B is equal to the sum of the heated floor area of all units A_u in the system. Furthermore, this is equal to the sum the heated floor area A_z of all the buildings in the system and equal to the sum of the heated floor area belonging to all floor area types in the system A_y . Lastly, this is also equal to the sum of heated floor area belonging to

all floor area classes in the system A_z and renovation states in the system A_r . This is described in Equation 8.

$$A_y(t) = \sum_b A_{b,y}(t) \quad (6)$$

$$A_z(t) = \sum_b A_{b,z}(t) = \sum_{y \in z} A_y(t) \quad (7)$$

$$A_B(t) = \sum_u A_u(t) = \sum_b A_b(t) = \sum_y A_y(t) = \sum_z A_z(t) = \sum_r A_r(t) \quad (8)$$

A.2 Energy model

The delivered energy to the building per energy carrier $E_{b,e}$ is equal to the delivered energy for the given carrier of all units $E_{u,e}$ belonging to the building. This is equal to the floor area of a unit A_u multiplied with the energy intensity of the given floor area type and carrier $E_{i,e,y}$ that the unit belongs to. This is shown in Equation 9. Delivered energy per floor area type to a given building $E_{b,y}$ is equal to the sum of delivered energy to all units $E_{b,u}$ in the building belonging to the given floor area type, as described in Equation 10. The delivered energy to a building per floor area class $E_{b,z}$ is equal to the sum of the delivered energy to all the floor area types $E_{b,y}$ that belongs to the given floor area class, as shown in Equation 11. Equation 12 describes that the total delivered energy to the building E_b is equal to the sum of the delivered energy to all units E_u belonging to the building. This is again equal to the sum of delivered energy from all carriers to the building, $E_{b,e}$.

$$E_{b,e}(t) = \sum_{u \in b} E_{u,e}(t) = \sum_{u \in b} A_u E_{i,e,y}(t) \quad (9)$$

$$E_{b,y}(t) = \sum_{u \in y} E_{b,u}(t) \quad (10)$$

$$E_{b,z}(t) = \sum_{y \in z} E_{b,y}(t) \quad (11)$$

$$E_b(t) = \sum_{u \in b} E_u(t) = \sum_e E_{b,e}(t) \quad (12)$$

Delivered energy is aggregated to the stock level, as shown in Equations 13-16. The delivered energy to the building stock per floor area type E_y is equal to the sum of delivered energy to all buildings in the stock for the given floor area type $E_{b,y}$, as given in Equation 13. Equation 14 describes that the delivered energy to the stock per floor area class E_z , is equal to the sum of the delivered energy to the given floor area class all buildings in stock, $E_{b,z}$. This is again equal to the sum of delivered energy to the stock given for all floor area types E_y , subject to the given floor area class. Delivered energy per energy carrier to the stock E_e is equal to the delivered energy to all units in stock for the given energy carrier, $E_{u,e}$. This is equal to the delivered energy to all buildings in the stock for the given energy carrier $E_{b,ec}$, the sum of delivered energy $E_{y,e}$ for the given carrier to all floor area types and the sum of delivered energy

for the given carrier $E_{z,e}$ to all floor area classes, as described in Equation 15. Equation 16 defines how the total delivered energy to the whole stock E_B is equal to the total delivered energy to all units in stock E_u , the total delivered energy to all buildings E_b , the total delivered energy to all floor area types E_y , the total delivered energy to all floor area classes E_z , the total delivered energy for all carriers E_e and the total delivered energy to all renovation states E_r .

$$E_y(t) = \sum_b E_{b,y}(t) \quad (13)$$

$$E_z(t) = \sum_b E_{b,z}(t) = \sum_{y \in z} E_y(t) \quad (14)$$

$$E_e(t) = \sum_u E_{u,e}(t) = \sum_b E_{b,e}(t) = \sum_y E_{y,e}(t) = \sum_z E_{z,e}(t) \quad (15)$$

$$E_B(t) = \sum_u E_u(t) = \sum_b E_b(t) = \sum_y E_y(t) = \sum_z E_z(t) = \sum_e E_e(t) = \sum_r E_r(t) \quad (16)$$

A.3 GHG-emissions model

The greenhouse gas emissions G are estimated based on the outputs from the energy model and input time series for carbon intensities I . The model allows for carbon intensities changing over time and given per year or per month for each energy carrier. The share of delivered energy that is electricity to appliances is given as α . Input is given per energy carrier e and results are calculated per carrier and time, as shown in Equation 17. It is then aggregated to total emissions from delivered energy to heat in Equation 18, electricity in Equation 19 and the total for the whole system in Equation 20.

$$G_e(t) = E_e(t) * I_e(t) \quad (17)$$

$$G_{B,heat}(t) = \sum_e E_{B,e}(t) * I_e(t) * (1 - \alpha_e) \quad (18)$$

$$G_{B,el}(t) = \sum_e E_{B,e}(t) * I_e(t) * \alpha_e \quad (19)$$

$$G_B(t) = \sum_e G_{B,e}(t) = G_{el}(t) + G_{heat}(t) \quad (20)$$

A.4 Coincidental analyses

Guan et al. (2016) define the coincidence factor S for a neighbourhood as given in Equation 21.

$$S = \frac{P_{tot,max}}{\sum_{i=1}^n P_{i,max}} \quad (21)$$

Where:

S = Coincidence factor of total neighbourhood energy use at observed years.

$P_{i,max}$ = The maximum electricity load or heating load of a building i .

$P_{tot,max}$ = The maximum electrical load or heating load of the neighbourhood.

n = The number of targeted buildings.

Guan et al. (2016) define the coincidental contribution of individual buildings to the whole neighbourhood as given in Equation 22.

$$S_i = \frac{P_i}{P_{i,max}} \quad (22)$$

Where:

S_i = Coincidental rate of building i to the neighbourhood peak at observed years.

P_i = A building's electricity load or heating load at the time of the neighbourhood peak.

$P_{i,max}$ = The maximum electricity load or heating load of a building i .



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