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Common approaches to find the energy saving potentials for the Norwegian residential buildings: a review study

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Abstract

Building sector is shown as a huge energy consumer worldwide. Therefore, a thorough understanding of energy performance in buildings is essential to propose and implement sustainable strategies for the future plans; and consequently, reach the low carbon emission targets. This study aims to investigate an approach to gather or generate large-scale energy data for Norwegian residential buildings. Also, approaches to visualize data and implement digital information tools are reviewed in this study. A qualitative literature survey was conducted to evaluate the relevant approaches/strategies for large data collection in the building sector. Results confirmed that building energy models could be suitable for generating consistent and detailed data. Elaborate and simplified engineering methods, statistical methods, neural networks and support vector machines, are widely used models. A hybrid model combining simulation-based techniques and machine learning algorithms shows promising results. An energy model class which simulates the physical relationship of processes at the building or end-use levels, which also utilizes cloud computing, could help generating generic energy models based on key performance indicators. The dataset can then be trained in a machine learning algorithm, which utilize historical information to attribute building energy use to particular end-uses and can predict different scenarios for the Norwegian building stock based on cadastre data and statistical data. The outcome of this study can help to introduce approaches to find the energy saving potentials in Norwegian buildings and present the suitable refurbishment strategies for future planning.

Keywords: Energy efficiency, Energy models, large-scale, top-down, bottom-up, black-box, white-box, literature study

1 Introduction

Transition of the European community towards sustainability is a combination of environmental, economic and social challenges that entails the adoption of strategic approaches across all sectors (European Environment Agency, 2020). The building sector accounts for 40% of the energy use (EPBD, 2010) and 36% of the CO_2 emissions (Artola et al., 2016), in addition existing buildings with low energy performance represent most of the European building stock (Almeida & Ferreira, 2017). It is estimated that at 85-95% of today's buildings will still exist by 2050 (European Commission, 2020b). The annual amount of deep renovations in the EU is only around 0.2% (Esser et al., 2019), for residential buildings the annual weighted energy renovation rate is estimated to be 1% (Artola et al., 2016). Energy efficiency is an essential component for reaching the EU Commission 2030 climate target plan (European Commission, 2020c). The plan seeks to reduce the emissions by 55% by 2030, compared to 1990 levels. In order to achieve the long-term carbon emissions targets, it is necessary to perform deep changes in the building sector (Almeida & Ferreira, 2017).

Considering the huge energy consumption in the existing old buildings, proper renovation plans can help to reduce energy use in buildings. Overall, buildings are long-lasting structures; their renovation needs large investments on and the development of long-term strategies considering a life cycle approach (European Commission, 2020b). Sustainable building renovation projects mainly aim to lower energy consumption in buildings incorporating low carbon solutions (Kylili et al., 2016). Such projects are focused on reducing the long-term costs and affordability. Renovation projects are also about improvement of health and well-being of the occupants (European Commission, 2020a). Sustainable building renovation projects are anticipated to increase the comfort levels and the quality of life for the occupants, while minimizing the negative environmental impacts and increasing the economic value (Kylili et al., 2016). However, to choose and implement the right sustainable strategy for future renovation plans, access to reliable data on the building performance is essential.

1.1 Scope of this study

This study aims to investigate 'how large-scale energy data can be gathered or generated for Norwegian residential buildings. Also, approaches to visualize data and implement digital information tools are reviewed in this study.

The outcome helps to introduce approaches to find the energy saving potentials in Norwegian buildings and present the suitable refurbishment strategies for future planning.

2 Method

This study was conducted through a qualitative literature survey, where the most relevant studies to the topic was reviewed and analysed. Oria and science direct were used as the main search engines. Regarding the literature selection criteria, only the English literature from 2010 to present in Europe were considered. The main search keywords and the number of studies found by each keyword are presented in Table 1. To include more relevant literature, some cited papers in the reviewed studies were also considered, even if they did not match the filtering criteria.

The reviewed studies and obtained information were rated on a five-point scale based on the relevancy to the topic (where 5 was very relevant and one was slightly relevant). This was later transferred to a literature matrix, presented in Table 2. The matrix consists of the author name, location and a summary of the reviewed studies.

Table 1: Search hits from Oria and ScienceDirect.

Search engine	**Topic**	**Hit**
Oria	Urban energy models	215 053
Oria	Building Information Modelling for existing buildings	179 823
Oria	Energy performance building sector	78 843
Oria	Historic Building Information Modelling	74 724
Oria	Building stock performance indicators	36 185
Oria	Key Performance Indicators existing building stock	19 089
Oria	BIM existing buildings	4 002
Oria	Sustainable Renovation Classification	2 489
Oria	Classifying building stock energy models	1 547
ScienceDirect	Historic Building Information Modelling	1 441
ScienceDirect	Performance indicators existing building stock	961
ScienceDirect	Classifying building stock energy models	499
ScienceDirect	Performance indicators renovation	483
ScienceDirect	BIM building stock	79

3 Literature study

Table 2 shows the matrix resulted from the literature survey. The table provides source, titles, content and location of the information in the papers. The relevant literature is further discussed in this section and categorized by building energy data with strategies, examples, visualization and digital tools, which is further discussed in the following sections.

Table 2: Literature matrix

Authors	Location	Summary
(Langevin et al., 2020)	Europe	- Presents a new energy model classification framework (leverages international modelling expertise from the participants of the International Energy Agency's Annex 70 on Building Energy Epidemiology). - Proposes a multi-layer quadrant scheme that classifies modelling techniques by their design (top-down or bottom-up) and degree of transparency (black-box or white-box) - Hybrid techniques are also addressed.
(Swan & Ugursal, 2009)	Worldwide	Two distinct approaches are identified: - *Top-down*, treats the building sector as an energy sink (focus on macroeconomic indicators) - *Bottom-up*, estimates energy consumption of representative individual buildings to regional and national sectors.
(Intelligent Energy Europe, 2009)	Europe	- Improves knowledge about the energy performance of the building stock, using the first IEE Project, Collecting DATA from Energy Certification to Monitor Performance Indicators for New and Existing Buildings (DATAMINE)
(Intelligent Energy Europe, 2012b)	Europe	- Presents a systematic approach to classify building stocks according to their energy related properties - A cross-country comparison, exemplary building for showcasing and national building stock models usage
(Intelligent Energy Europe, 2016a)	Europe	- Takes building typologies defined according to the TABULA approach as a basis for building stock monitoring activities - Tracked the progress of energy performance of building entireties regarding energy saving and climate protection targets – to trigger enhanced or corrective actions by the involved key actors in European Housing Stocks.
(Khodeir et al., 2016)	Egypt	- Integrates HBIM tools for sustainable retrofitting of heritage buildings through a conservation framework - Provides literature review and qualitative analysis of worldwide examples
(Murphy et al., 2013)	Europe	Proposes a new methodology for the HBIM for historic structures and environments involving the following stages: - collection and processing of laser/image survey data

		- identifying historic detail from architectural pattern books - building of parametric historic components/objects - correlation and mapping of parametric objects onto scan data and the final production of engineering survey drawings and documentation
(Visscher et al., 2016)	Europe	A review from several European studies concluded that: - the energy saving targets based on renovation of the housing stock cannot be reached with the current renovation practices - there is a need to find ways to significantly increase the renovation rate and depths tremendously or to reduce the expectations on what can be reached by reducing the energy demand in the existing dwellings
(Sandberg et al., 2016a)	Europe	- shows that future trends for construction, demolition and renovation activities lead to similar patterns emerging in all countries - The model estimates future renovation activity due to the stock's need for maintenance as a result of ageing - 78% of all dwellings are shown to benefit from energy efficiency measures by 2050, either as they are constructed (31%) or undergo deep renovation (47%)
(Brattebø et al., 2016)	Norway	- Shows typical effects of energy measures for existing housing in Norway.
(Mata et al., 2013)	Europe, Sweden	- Presents the Energy, Carbon and Cost Assessment for Building Stocks (ECCABS) model, which is a model to assess energy-saving measures and carbon dioxide mitigation strategies in buildings - Energy usage and CO2 emissions in Swedish residential sector are shown to be reduced by 55% and 63%, respectively, with most of the measures being cost–effective
(Sartori et al., 2016)	Norway	- Shows a model based on dynamic material flow analysis, general in its principles, applied to the dwellings stock in Norway - Technical parameters (e.g. dwellings lifetime and renovation cycles) are expressed by probability functions
(Sandberg et al., 2016b)	Norway	- Confirms that a historical shift to more efficient energy carriers and heating systems has influenced energy savings in the system - The total average energy savings per m2 are offset by changes in user heating habits - A significant decrease is shown in average delivered energy intensity per m2, only after the introduction of heat pumps
(Sandberg et al., 2014)	Norway	- Shows a segmented dynamic dwelling stock model for understanding the nature of the long-term development in stocks, their turn-over and need for maintenance, including a case study for Norway - Segments are defined by dwelling type and construction period - In Norway, detached houses constructed between 1945 and 2011 will dominate the renovation activity in the coming decades
(Vieites et al., 2015)	Europe	- Presents some major projects carried out in Europe and their achievements regarding the integration of innovative technologies and use of different sources of renewable energy in existing buildings

(Pombo et al., 2016)	Worldwide	- Provides a critical review of the research undertaken on housing retrofits and discusses the approaches driving the assessment of energy efficiency measures around the world - Building envelope insulation, window replacements, and air sealing are shown as the most common strategies under consideration - There is a need to apply a life cycle approach in order to find optimal retrofitting solutions and improvement potential of housing renovation
(Jäger, 2012)	Europe	- A book about the current existing building stock. What measures can be done and several examples.
(Ascione et al., 2017a)	Naples, Italy	- Studies how to predict building energy performance with low computational power and good reliability using artificial neural networks. - Proposed methodology can give a significant support to rigorous approaches for planning building energy retrofit, e.g. those based on cost-optimal analysis or building performance optimization
(Alves et al., 2018)	Belo Horizonte, Brazil	- Develops a comprehensive framework to identify and analyse the energy saving potential of existing building stock. - Cost effective energy savings of up to 24% can be possible in the high-rise office building stock by 2036
(Ascione et al., 2017b)	Italy	- Investigates the large-scale energy retrofit of a significant share of Italian public administration buildings - High building energy performance can be achieved through three main levers: proper thermal design of the building envelope, efficient HVAC and primary energy systems; exploitation of renewable energy sources - For existing buildings, a good strategy is postponing the third lever to the retrofit of envelope and HVAC systems

3.1 Energy models

There have been multiple efforts to classify existing building stock regarding to condition and energy consumption. The building characteristics are complex and is hard to model. Due to more ambitious goals, access to big data and greater computational power we are now able to simulate more complex data structures. In this section building energy models and building stock classification schemes are investigated.

3.1.1 Swan and Ugursal classification scheme

To date Swan and Ugursal (2009) classification has gained wide acceptance among building stock energy modelers. Two distinct approaches are identified: top-down and bottom-up. The top-down approach treats the building sector as an energy sink with focus on macroeconomic indicators and is not concerned with individual end-uses. The bottom-up approach estimates energy consumption of a representative set of individual buildings to regional and national sectors. Figure 1 shows an overview of the classification updated by Li et al. (Swan & Ugursal, 2009).

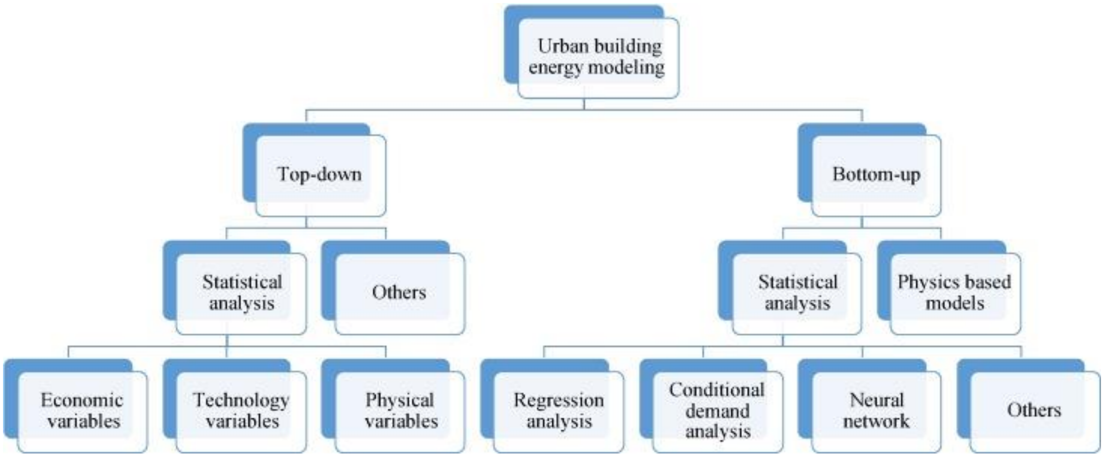


Figure 1: Top-down and bottom-up modelling techniques for estimating the regional or national energy consumption (Li et al., 2017).

3.1.2 Updated classification scheme

A new proposed building stock energy model classification scheme has been introduced by Langevin et al. (2020). It divides building stock energy modelling into four quadrants (Q) based on their design (top-down/bottom up) and degree of transparency (black-box/white-box) as shown in Figure 2. It includes examples of emerging data-driven and simulation-based techniques alongside established techniques such as machine learning algorithms. Sub-layers representing key energy use determinants which could be mapped to the same four quadrants as shown in the energy layer. The model builds from existing classification frameworks while accounting for emerging simulation-based modelling techniques and recognizes the potential sub-layers of a building stock energy model (Langevin et al., 2020).

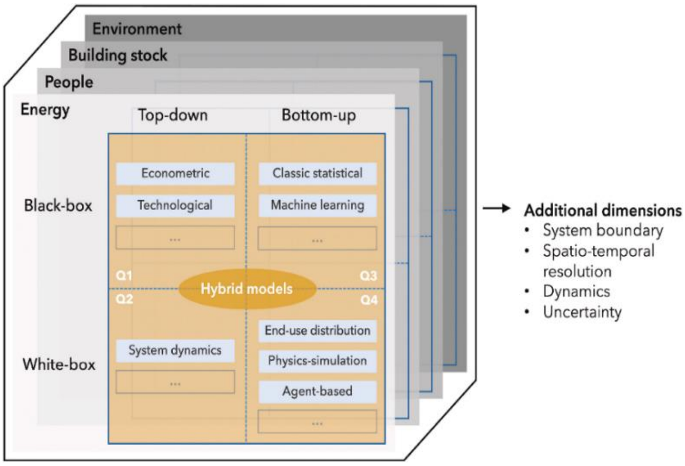


Figure 2: Classification scheme for building stock energy models (Langevin et al., 2020).

The first quadrant, Q1 estimates building stock energy, utilizing available sector-wide historic variables such as demographics or economic indicators. The model typically excludes end-use energy attribution and rely on aggregate end-use functions. The economic indicator includes demographics, fuel prices, household income, or the gross domestic product of an economy as a whole. Technological models account for technological characteristics of the building stock (Langevin et al., 2020).

The second quadrant, Q2 represent physical causality at the aggregate building and technology stock level. This model is characterized by quantitative models of aggregate-level building and technology stocks and flows which can be annual alterations to the residential stock from construction, retrofits and demolition.

The third quadrant Q3 utilize historical information to attribute building energy use to particular end-uses. Classical statistical techniques are used to predict either whole building or end use energy consumption with regression-based and conditional demand analysis. Machine learning techniques utilize a wide range of algorithms to find patterns in rich and large datasets. These models have seen a large increase in the literature over the last decade.

The last quadrant Q4 simulates the physical relationship of processes at the building or end-use levels, which include high-performance and cloud computing along with simulation-based techniques. The end-use distribution models the distribution of energy demand per end-use or appliance type to calculate total end-use or appliance energy consumption at scale. This is done without interactions between end-uses. The Agent-based models use software representations of individual buildings and decision-maker agents that have rules for interacting with other agents and their physical or economic environments. Physics-simulation include archetype modelling which is a well-established physics-based approach. This model simulates the energy performance of a single building or collection of buildings. The results can be scaled up to represent total sector energy use in a defined geographic area (Langevin et al., 2020).

There are also many hybrid models that use mixed approaches across the quadrants. Many of these hybrid models rely more heavily on one of the classification quadrants and have some inputs from others (Langevin et al., 2020).

For the bottom-up approach many calculations are needed to evaluate the building energy system, from sub-system level to building level and even regional or national level. There will be a problem due to the different application in use of existing simulated building data. Each model has its own advantages in certain cases of applications. In the case of predicting building energy, the model can adopt some simplifying strategies, it can become a light-weight model and is easy to develop while maintaining accuracy (Zhao & Magoulès, 2012). By implementing Artificial Neural Networks and Support Vector Machines a statistical model can give highly accurate prediction as long as model selection and parameters setting are well performed and sufficient historical performance data exist (Zhao & Magoulès, 2012). Use of machine learning techniques also shows promising results in renovation projects. A study (Ascione et al., 2017a) shows how to predict building energy performance with low computation and good reliability using artificial neural networks. The proposed methodology can give a significant support to rigorous approaches for planning building energy retrofit based on cost-optimal analysis or building performance optimization (Ascione et al., 2017a).

An advantage for the top-down method is the limited input information which is often aggregated with economic data, sociodemographic and market economic effects. A limitation is the requirement of long-term historical data and technological details (Li et al., 2017). In more recent years the potential on Life Cycle Assessment (LCA) of building stock has been highlighted. Geographic Information System (GIS) integration is promising to explicitly consider spatial constraints and localize the hot spots, this can be areas with high potential of emissions reductions if refurbishment actions are put in place or areas with high material concentrations. It is suggested that research is done on calibration of building stock models, integration of GIS and 3D semantic models for improved description of the building stocks, integration of dynamic material flow analysis for the inclusion of dynamic evolution (Mastrucci et al., 2017). For calculating energy demand of the LCA studies the engineering-based method is commonly applied. The limitations and impact of these models are stated in the above section.

3.1.3 Existing building data

One strategy for building renovation is to analyse the existing building stock. This was done by the Intelligent Energy Europe from 2006 to 2016. The goal of the first IEE Project, Collecting DATA from Energy Certification to Monitor Performance Indicators for New and Existing Buildings (DATAMINE), was to improve the knowledge about the energy performance of the building stock. The collected 19 000 datasets from 12 different European countries between 2006 and 2008 were analysed and compared. For different age and size groups "average buildings" were defined which are representative for the respective sample subsets (Intelligent Energy Europe, 2009).

The second project, Typology Approach for Building Stock Energy Assessment (TABULA), was launched in 2009 based on the DATAMINE project, the idea was to make an agreed systematic approach to classify building stocks according to their energy related properties. This was done for cross-country comparison, exemplary building for showcasing and for national building stock models usage. It was concluded that an energy saving of over 45 % can be reached, even with the standard refurbishment (Intelligent Energy Europe, 2012b; Loga et al., 2016).

Energy Performance Indicator Tracking Schemes for the Continuous Optimisation of Refurbishment Processes (EPISCOPE) takes building typologies defined according to the TABULA approach as a basis for building stock monitoring activities (Intelligent Energy Europe, 2016a). The main objective is to track the progress of energy performance of buildings with regards to energy saving and climate protection targets, in order to trigger enhanced or corrective actions by the involved key actors in European Housing Stocks (Intelligent Energy Europe, 2016b). For the case of Norway, they concluded that the most sensitive input parameters is population and lifetime of dwellings, which also were the input parameters of highest uncertainty (Sandberg et al., 2016a).

3.1.4 Examples of large-scale energy models

Urban 3D models offer great support for establishing climate protection concepts by allowing to quantify measures to improve energy efficiency and integrate renewables. There are some software’s available for calculating large-scale energy models. One of these is CityGML which can model buildings with 4 different Levels of Details (LoDs).

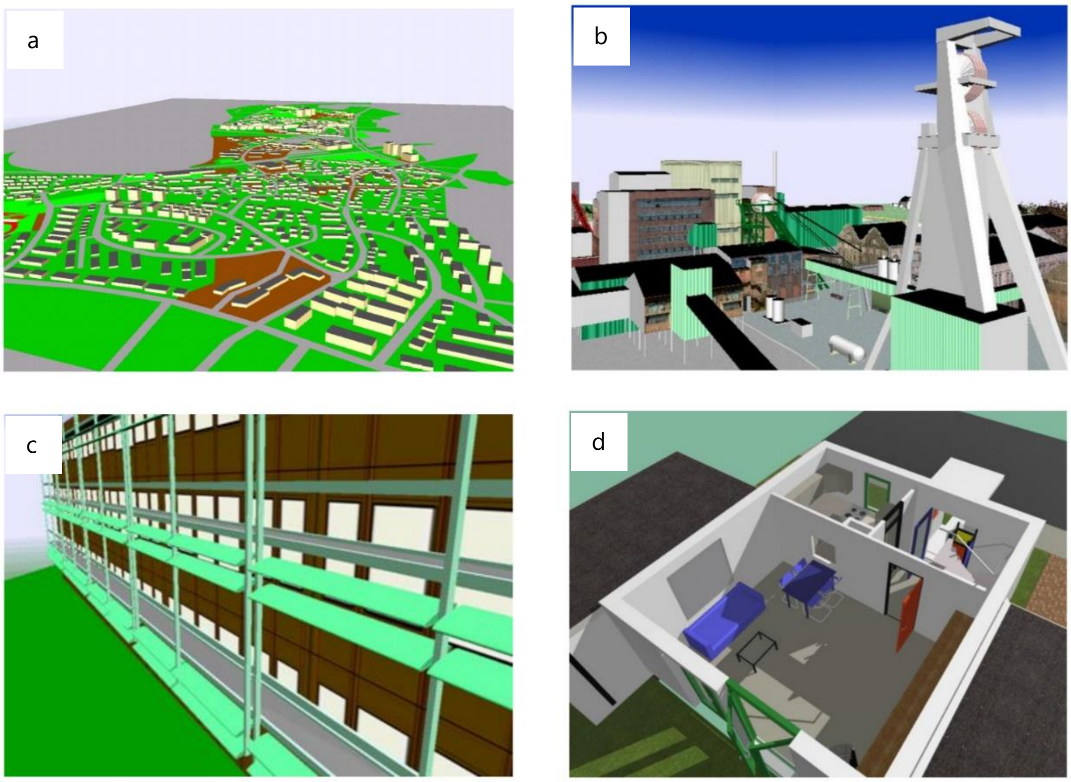


Figure 3: Examples of large-scale building models with LOD1 (a), LOD2 (b), LOD3 (c), and LOD4 (d) (Gröger et al., 2012).

LoD1 models buildings as a cube with flat roofs, LoD2 adds the details of roof shape. In LoD3 the details of exterior surfaces like windows and doors are added and LoD4 models the interior surfaces as well, see Figure 3**Error! Reference source not found.** (Gröger et al., 2012).

A case study of Ludwigsburg using SimStadt with LoD1 and LoD2 with almost 177,000 buildings showed that 1°C reduction in the set-point temperature and set-back temperature of the public buildings resulted in 109 GWh annual energy saving (Eicker et al., 2018). The heating energy could be reduced by up to 58% by applying the highest refurbishment standard scenario. The most important requirements for replication of the results are 3D city models with valid solid geometry per building and basic attribute data such as year of construction (YoC) and building usage. Figure 4 shows an example of a similar project. It is very challenging to get detailed and reliable consumption data to validate the simulation results (Eicker et al., 2018).

Figure 4 Overview of the heating demand for a large-scale energy project similar to Ludwigsburg (hft-stuttgart, 2018) .

Form a study in Italy with a bottom-up engineering methodology conducted by Fracastoro & Serraino (2011), statistical distribution of buildings according to primary energy for heating demand had been obtained from Census data with integration of local standards, laws and energy statistics (Fracastoro & Serraino, 2011). The procedure is applicable to any location/region where the data size is large enough so it can be described by a complete and dedicated set of Census data, and small enough so it can guarantee a sufficient homogeneity under the climatic and building technology points of view. This method has been used to define the performance scale for energy certification and to evaluate the energy saving potential of large scale retrofit actions on the building envelope. Building energy cadaster may be obtained from a reliable energy certification in the future. The global overview of the building stock energy performance may provide further insight for the decision-makers and local or state authorities (Fracastoro & Serraino, 2011).

A German study conducted by Zirak et al. (2020) show applying a statistical year of construction (YoC) of a building can lead to an acceptable heating demand calculation of the entire city. This may not be accurate enough at building level. The focus was residential buildings and tested for two German cities. The YoC is an important parameter for the heating demand calculation of buildings in a district. These calculations can help decision-makers and urban planners when developing energy efficiency or climate protection concepts (Zirak et al., 2020).

The Energy Efficiency for EU Historic Districts' Sustainability (EFFESUS) was established in 2012 and the goal was to investigates the energy efficiency of European historic urban districts (Frick et al., 2013). This was done by develop and demonstrate through case studies a methodology for assessing and selecting energy efficiency interventions with a decision support system (Kariotellis, 2015). A multiscale data model with data from several cities from Spain, Sweden, Budapest, Turkey, Italy, Germany and UK was developed for the management of energy in addition to a new non-invasive, reversible yet cost-effective technology for significantly improving thermal properties was developed (Frick et al., 2013). Seven study cases are included in the project where the urban interventions consist of implementation of new and existing technologies at urban district level, such as smart grids, PV and energy storage. The building consist of application of new and existing products and systems at building level, including aerogel insulation, traditional passive solutions, improved indoor climate control systems, and secondary glazing/windows (Lucchi et al., 2017; Becherini et al., 2018).

Within the EFFESUS project 77 Energy Conservation Measures were analysed to determine their impact on heritage significance. A Heritage Impact Assessment combined with the economic assessment and applicability of energy conservation Measures, can provide support to authorities and local decision-making processes regarding the sustainability of a historic district (Grun et al., 2013; Egusquiza et al., 2018). Studies shows that examining the recurrent characteristics of historic architecture in a local context may promote energy improvements compatible with the material and aesthetic conservation of historic buildings (Genova et al., 2017).

3.2 Building indicators

Building renovation project is affected and depended on a long list of aspects. In use of different classification schemes, one needs to define a set of parameters whom fit the boundaries of the project. Indicators on the existing building stock is needed in order to find out which buildings are most suitable for conducting smart renovation, it can be under construction to manage and keep track of the progress, and after renovation is conducted to see if we have reached our benchmark and goals. It is important to have well defined boundaries and performance indicators to have a successful refurbishment project.

3.2.1 Performance Indicators

Key Performance Indicators (KPI) reflect a goal and provide means for the measurement of the progress towards those goals for further learning and improvements. This is often used for project managers to keep track of the progress of a project but is also suited for evaluating a set of benchmarks for energy models. Eight generic categories for the performance of buildings have been identified, these employ a range of KPIs for their performance measurement, which are economic, environmental, social, technological, time, quality, disputes and project administration. Energy is the largest sub-category of them all under the environmental category and has 17 key performance indicators. Most of these address electrical energy consumption, peak demand and savings in form of return ratio and payback time. In addition, site orientation to maximise passive solar potential and utilisation of renewable sources can be found as measurements in different studies. With aspect to indoor comfort, thermal performance and use of daylight is also addressed in this sub-category. Although overheating risk, indoor quality and visual comfort are also found in separate sub-categories (Kylili et al., 2016).

There is not a common consensus on the definition of sub-categories, nor a standardised approach or methodology, not even regulations or guidelines for undertaking the assessment of each. The gap is created due to the lack of a sustainable building standardised basis, which will be established on a set of relevant well-defined performance indicators, for national and international building policies. This challenge is anticipated to be addressed through the work of research initiatives and innovative research projects in the coming years (Kylili et al., 2016). This can be certification systems such as the Building Research Establishment Environmental Assessment Method (BREEAM) which is a sustainability rating scheme for the built environment. Through its application and use, BREEAM helps clients to measure and reduce the impacts of their buildings and in doing so, create higher value, lower risk assets that are better for people and the environment. The BREEAM Refurbishment and Fit Out (RFO) standard enables real estate investors, developers and building owners to assess sustainability-related impacts during the design and works of a refurbishment or fit out project. These have separate well defined performance Indicators categorized in the same way as the KPI (Building Research Establishment, 2015).

There is a large potential for cost effective renovations that reduce both carbon emissions and non-renewable primary energy use. The evaluation of the benefits from energy related renovation programmes and policies focusses mainly on energy savings. This leads to the underestimation of the positive impacts and co-benefits such as visual and thermal comfort to the inhabitants of the buildings and to society. This may lead to sub-optimal investment decisions and policy design. Energy specialists tend to focus solely on energy-related effects and professionals from other fields (such as health professionals or economists) are unlikely to be consulted in the context of building renovations. This means that information to increase the perception of co-benefits, as well as interdisciplinary cooperation, is needed to fully take into account the extent of the non-energy benefits and to let them influence investment decisions and policy design (Almeida & Ferreira, 2017).

3.2.2 Readiness Indicators

In addition to KPI’s for benchmarking the progress and goals it is important to have indicators for measurement of the readiness. The 2018 revision of the European Energy Performance of Buildings Directive (EPBD) aims to further promote smart building technologies, in particular through the establishment of a Smart Readiness Indicator (SRI) for buildings (European Commission, 2020d). The indicator is an informative tool, the objective is to raise awareness about the benefits of smart technologies and Information and communications technology (ICT) in buildings, in particular from an energy perspective. Smartness of a building refers to the ability of that building or its systems to sense, interpret, communicate and actively respond in an efficient manner to changing conditions. This is in regard to the operation of technical building systems or the external environment, including energy grids, and to demands from building occupants (Märzinger & Österreicher, 2020). The SRI key functionalities is technological readiness assessment of a building capacity to adapt to user needs and energy environment, evaluation of building readiness in operating more efficiently and measurement of the readiness of building interaction in demand response with the energy system and the district infrastructure (Vigna et al., 2018).

SRI also is aimed at providing an indication of how well buildings can interact with the energy grids. Load shifting across buildings has an important role to improve efficiency and the integration of renewable energy systems. Current proposals for the SRI focus mainly on qualitative appraisals of the smartness of buildings and do not include the wider context of the districts. Quantitative approaches that can be easily applied at an early planning stage are still missing. To optimize infrastructure decisions on a larger scale, a perspective beyond the building level is necessary to evaluate and leverage the larger load shifting capacities (Märzinger & Österreicher, 2020).

A study from Finland was set to provide the first insights into the applicability of the SRI in cold climate countries. Because of the advanced information and communication technology and high building energy consumption profiles, the Northern European countries were interesting test environment for the indicator. It was found that the baseline design for the European SRI is not directly feasible for cold climate countries. The applicability could be improved by reconsidering the realization of the selection of the SRI relevant building services in practical experiments (Janhunen et al., 2019).

3.3 Digital tools and data visualization

Often the decision-makers are non-technical and have not enough insight in the underlaying simulations and data fabrication. It is important to be able to visualize data and consider the knowledge of different end-users by including multiple data layers. Several methods have been proposed to evaluate the specific energy use of the existing building stock. From large number of Census and cadastre data or from actually monitored data. Methodologies based on Geographic Information System (GIS) techniques has also been assessed, which can integrate geometrical Census data, and adapt the methodology to the desired detail level (Fracastoro & Serraino, 2011).

3.3.1 Historic Building Information Modelling

Historic Building Information Modelling (HBIM) is a library of objects, based on historic architectural data. These objects are cross platform available and consist of geometric descriptive language which is made by parametric mapped objects from point cloud and image survey data. The final stage in the reverse engineering process is to plot the parametric objects onto the laser scan surveys as building components to create or form the entire buildings. HBIM can automatically create details and cut sections in addition to the 3D models for both the analysis and conservation of historic objects, structures and environments. This can help engineers with rapid and accurate building energy models of existing buildings for final production of drawings and documentation (Murphy et al., 2013). It was found that applying both HBIM and sustainable retrofit on heritage buildings in Egypt was still limited and faces a number of challenges such as unavailability of equipment, limited availability of professionals, and funding and financial-related challenges (Khodeir et al., 2016).

A tool was launched from the TABULA project displaying the building energy related features and the possible energy savings by implementing refurbishment measures, see Figure 5. This was based on combination of existing data from several countries and allowed users to see possible energy savings by implementing refurbishment measures (Intelligent Energy Europe, 2012a).

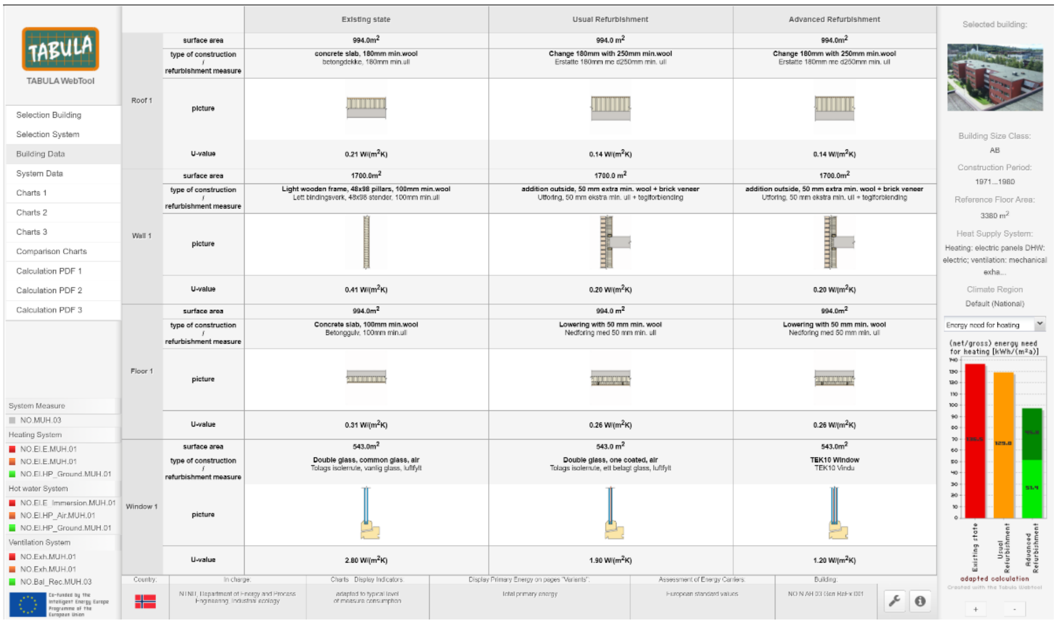


Figure 5: The TABULA WebTool allowing users to see possible energy savings by implementing refurbishment measures (Intelligent Energy Europe, 2012a).

3.3.2 Data visualization

The EU Building Stock Observatory (BSO) was established in 2016 as part of the Clean energy for all Europeans package and aims to provide a better understanding of the energy performance of the building sector through reliable, consistent and comparable data. The data published in the BSO can be very useful to policymakers, investors, stakeholders, local and national authorities and researchers. Historic data is organized according to ten thematic areas: building stock characteristics, building shell performance, technical building systems, nearly Zero-Energy Buildings, building renovation, energy consumption, certification, financing, energy poverty, energy market (Arcipowska A. et al., 2014).

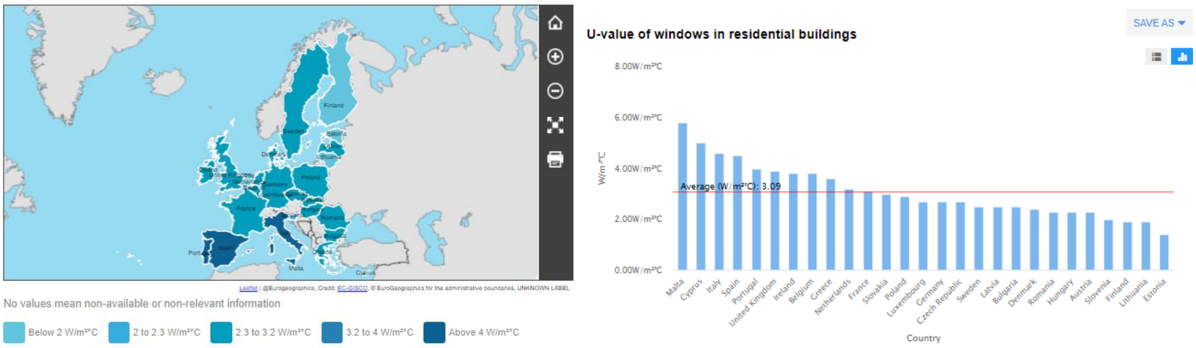


Figure 6: EU Buildings Datamapper interface (EC-GISCO, 2020).

Multimap is developed by Multiconsult and is a tool for mapping performance of building portfolios, such as technical condition of buildings, adaptability and usability as an input to strategic planning. This can be used on a larger scale with a top-down approach. This project led further to the research project Oscar value which focuses on develop knowledge, methods and tools to enable development and achieve sustainable buildings and value creation for owners and end-users (Temeljotov-Salaj et al., 2015). This can also be implemented with the Norwegian start-up company Endrava is focusing on the carbon capturing potential in Europe for sectors such as industry, power and heat and waste to energy. This is done by a top-down approach where large quantities of public data on emissions at European level are proceeded and quality-checked and combined with other relevant public and private databases. See Figure 7 for the overview of the tool (CaptureMap, 2020). This could also be transferred to energy savings potential for existing building.

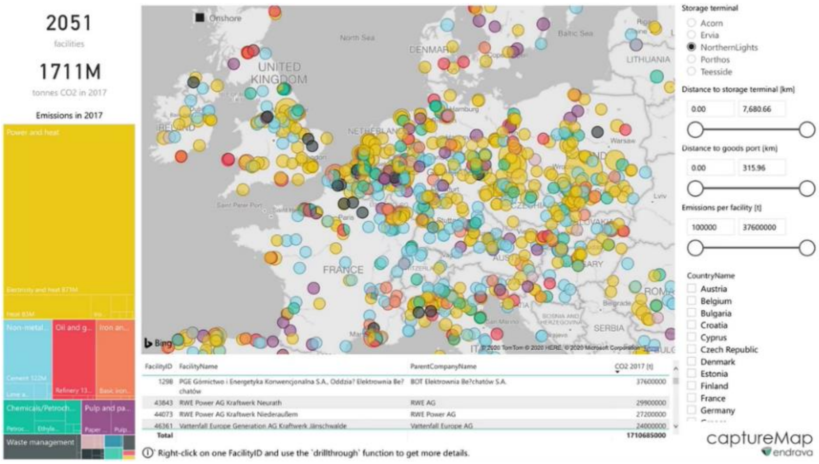


Figure 7: CaptureMap main dashboard and facility details (CaptureMap, 2020).

The Buildt Stock Explorer is an online tool for interactive analysis and modelling of the Norwegian building stock with aspect to energy use, year of construction, size and other metrics. It is currently being developed and more data and methods for modelling and statistical information are yet to come (Zhuravchak et al., 2019).

Figure 8: 3-dimensional scatter plot of sample subset form Built Stock Explorer (Zhuravchak et al., 2019).

4 Results and discussion

To investigate the potential for white-box/black-box and bottom-up/top-down approaches for large-scale energy models in Norway, the existing Norwegian residential building stock and the different energy model approaches are focused as the first step of the analysis.

4.1 Norwegian residential building stock

The building data is collected from the Statistics Norway's Information Centre (SSB) (SSB, 2021). Such data is often generated from different catalogues and need to be post-processed. For large datasets this can be a tedious task, especially for usage in data simulation. Enova is owned by the Norwegian Ministry of Climate and Environment and contributes to reduced greenhouse gas emissions, development of energy and climate technology and a strengthened security of supply (Enova, 2021). Enova also have data which may be suitable for building energy data generation, this data is not publicly available but should be investigated for later work.

The data gathered from SSB show the Norwegian building stock consist of in total 2 610 000 residential houses, almost half of these are detached houses, 25 % are apartments, the rest consist of Semi-detached house and chain houses. There is in total 383 000 (38 %) residential houses built before 1940 and 1 300 000 (54 %) houses built between 1940 to 1990 (SSB, 2020). According to Figure 9, 67 % of the detached houses were built between 1940-1990 and 17 % where built before 1940. There is a peak in detached houses in 1980 and has been a decline since then. Building apartments has on the other hand had an increase since 1990 (SSB, 2020).

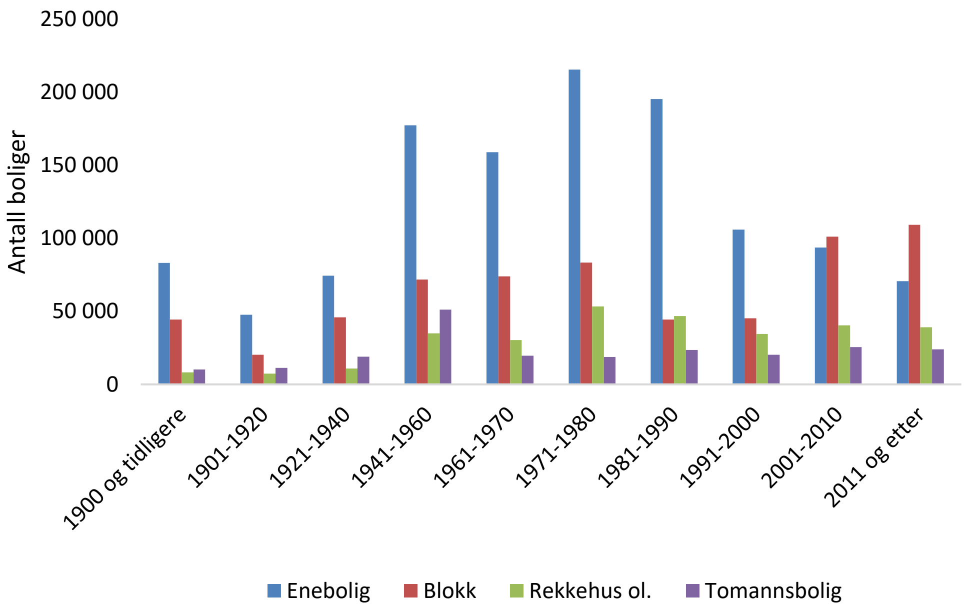


Figure 9: Distribution of residential buildings by age. Blue: Detached houses, Red: Apartments, Green: Chain houses, Purple: Semi-detached (SSB, 2020).

The energy usage is heavily impacted of the location and local climate. Therefore, have we investigated where in Norway most of the residential buildings are located. According to Figure 10, most of the buildings are in Oslo, Viken and Vestlandet, in total 1 480 000 (60 %). In addition, the majority of building apartments (76 %) are located in this region. Detached houses are scattered across all regions.

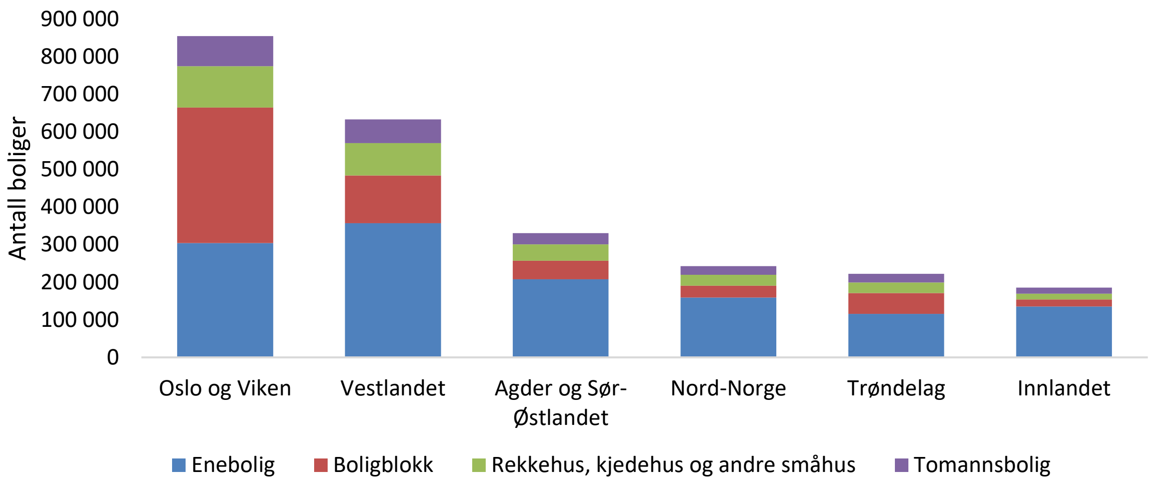
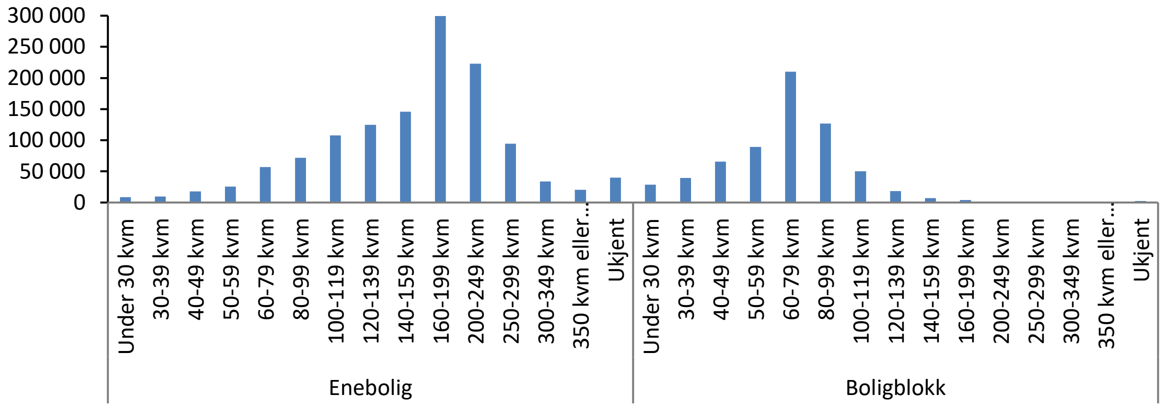


Figure 10 Distribution of residential buildings by region in Norway. Blue: Detached houses, Red: Apartments, Green: Chain houses, Purple: Semi-detached (SSB, 2020).

There is no consistent or available data on specific floor area for different building types and ages combined. We can see the floor area distribution on Figure 11 for the different building categories. Most of the detached houses has floor area between 140-250 m^2, apartments have smaller floorplan around 60-100 m^2. Semi-detached houses have an even distributed floor area between 60 – 200 m^2 and chain houses between 60 -140 m^2.



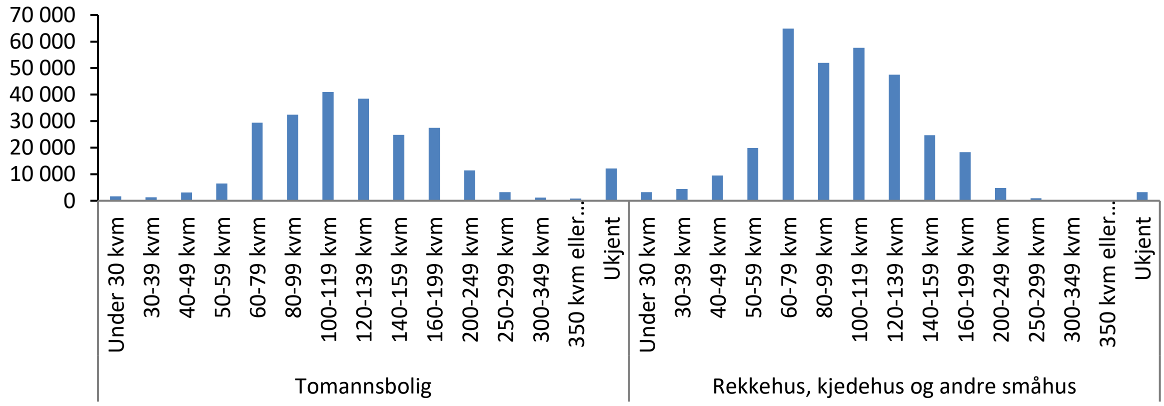


Figure 11 Distribution of residential buildings by floor area (SSB, 2020).

4.2 Energy model approaches

There are several studies presenting different approaches for generating quality energy data for existing buildings. Swan and Ugursal outlined classification scheme which has gained wide acceptance from large-scale energy modellers. One of the suggested approaches is to simulate individual buildings models, which later can be assembled to a large-scale energy model. It is an approach which is computationally demanding, where many variables must be integrated, and detailed models must be established. Simplification of large-scale building models has been conducted, where models from Ludwigsburg show that it is possible to generate data based on 3d city models and statistical data such as year of construction. It is important that these 3d models consists of valid solid geometry and not a mesh, which most scanned 3d models are. In addition, it is not mentioned how the model incorporate window size and properties, since the SimStadt tool only accounts for LoD1 and LoD2, which means it accounts for details such as building shape.

Often lack of quality existing data makes is difficult for use in energy modelling. There have been some initiatives from IEE for gathering (DATAMINE), classifying (TABLUA) and tracking (EPISCOPE) energy data for use in refurbishment projects. There are some approaches for combining both computer generated and existing building data which seems promising. The approach indicates usage of either simulated models which has been generated over a decade or constructing of new data models, which can be combined with actual energy data for comparison. In use of complex data models and machine learning, it is important to have sufficient amount of high-quality data and the right variables. This means for a hybrid model with combination of machine learning techniques and physics-based simulations, one needs to define a set of variables form the generation of generic white-box energy models which are suitable for a black-box machine learning algorithm. Picking the right indicators depends on the usage of the data. There should also be integrated robustness and resilience parameters so we can find deviations on which input parameters that has greatest impact.

Visualization is an important factor when working with large-scale data models. Often the decision-makers are non-technical and have not enough insight in the underlaying simulations and data fabrication. Therefore, are we in need of analytical tools which can provide us with an overview on different detail levels. The EU Building Stock Observatory Datamapper can be somewhat lacking updated data, since many countries is missing central data such as building performance and construction year. It would also be interesting to have more customizing control for the visualized data.

4.2.1 Q1 Black-box/Top-down approach

This Black-box/Top-down approach estimates aggregate building energy use from sector wide economical or technological variables. These variables could be retrieved and generated with data from SSB or Norwegian Government Agency for Administration and Financial Management (DFØ). This model is simple and computationally tractable, readily paired with other modelling frameworks with example bottom-up representations of energy demand in Integrated Assessment Models. The limitation of this approach is typically unable to represent impacts of specific technology or operation improvements and unable to represent disruptive changes to building stock energy use due to reliance on historical data.

4.2.2 Q2 White-box/Top-down approach

The white-box top-down approach represent physical causality at the aggregate building and technology stock level. This could be data collected from EU Building Stock Observatory and Intelligent Energy Europe for buildings in Europe. More specific data for Norway can be gathered from Enova or SSB. The strength of Q2 is to be able to represent the complexity of building stock energy use and its components at the aggregate level, including technology and building stocks and the evolution of the system over time. It is difficult to link aggregate building energy use to building level operations. Meaning for example that we know the total energy consumption, but we don't know the distribution with aspect to heat loss or other energy measures. It is also a challenging to represent spatial dimension, which also may require extensive data, time, and expert knowledge to fully represent system components.

4.2.3 Q3 Black-box/Bottom-up approach

The black-box bottom-up approach can represent the complexity of building stock energy use and its components at the aggregate level, including technology and building stocks and the evolution of the system over time. It is a somewhat more abstract approach which can be lacking some structure in the model and details on the building stock. There has been some scepticism for use of black-box models due to the lack of transparency. We have found more acceptance for machine learning techniques among building modelers in recent time. The Q3 approach is facing some of the same problem as the Q1 approach with being able to link aggregate building energy use to building operations level. There is a challenge to represent spatial dimension which may require extensive data.

Fracastoro and Serraino (2011) studied statistical distribution of buildings according to primary energy for heating demand (E-SDOB). Which had been obtained from Census data with integration of local standards, laws and energy statistics. The procedure is applicable to any location/region where the data size is large enough so it can be described by a complete and dedicated set of Census data and small enough so as to guarantee a sufficient homogeneity under the climatic and building technology points of view. This method has been used to define the performance scale for energy certification and to evaluate the energy saving potential of large scale retrofit actions on the building envelope. Building energy cadastre may be obtained from a reliable energy certification in the future. The global overview of the building stock energy performance may provide further insight for the decision-makers and local or state authorities (Fracastoro & Serraino, 2011).

4.2.4 Q4 White-box/Bottom-up approach

The Q4 approach is the most common approach for individual energy models. It simulates the physical relationships of processes at the building or energy end use level. The approach is useful to explicitly represent key dynamics influencing building energy end uses, building stock diversity, and the aggregate energy effects of changes to operations at the individual building level. It is found in the literature that standalone end-use distribution models are uncommon. The model requires extensive data to represent detailed characteristics of the building stock and drivers of its end use patterns, computationally intensive, potentially challenging to pair with other modelling frameworks. The data models are also time-consuming to build, and human errors may occur. Most of the studies found from the literature is related to the white-box modelling. This was done by the TABULA project found in the literature study. Methodologies based on Geographic Information System (GIS) techniques is a rapidly developing physics-modelling.

Eicker et al. (2018) established urban 3D models which offered great support for climate protection concepts by allowing to quantify measures to improve energy efficiency and integrate renewables. A case study of Ludwigsburg with almost 177,000 buildings showed that 1°C reduction in the set-point temperature and set-back temperature of the public buildings resulted in 109 GWh annual energy saving. The heating energy could be reduced by up to 58% by applying the highest refurbishment standard scenario. The most important requirements for replication of the results are 3d city models with valid solid geometry per building and basic attribute data such as year of construction (YoC) and building usage. It is very challenging to get detailed and reliable consumption data to validate the simulation results (Eicker et al., 2018). A Germany study show applying a statistical year of construction (YoC) of a building can lead to an acceptable heating demand calculation of the entire city. This may not be accurate enough at building level. The focus was residential buildings and tested for two German cities. The YoC is an important parameter for the heating demand calculation of buildings in a district. These calculations can help decision-makers and urban planners when developing energy efficiency or climate protection concepts (Zirak et al., 2020).

4.2.5 Hybrid approach

A hybrid approach combines elements of the models across the four classification quadrants. It can rely on one specific quadrant and have some inputs from others or have an equally weighted input from both or all. The hybrid approach may address the limitations of one quadrant by complementing with the strengths of another. It is more flexible in application and able to answer a broader set of analysis questions. This can for example be a combination of top-down statistical data from SSB and generic bottom-up energy models. This may also lead to more complex model in design and implementation, which makes it more difficult to communicate and replicate.

The literature indicates that Q1 and Q2 is most common combined with Q3 and Q4 when using models for future predictions. This seems like a god way to integrate both macro and micro changes in the energy models, meaning generated generic models can consider population growth and building replacement rates. The Smart Readiness Indicator (RSI) could be an interesting implementation for indication of how well buildings can interact with the energy grids on a large-scale. Especially considering peak energy demand in the residential housing marked and the integration of new energy tariff in Norway. Which consider both energy consumption and peak energy demand.

4.3 Suggested approach

Using the bottom up methodology from Swan and Ugursal with a combination of statistical analysis and physics-based models seems promising for analysing the current building stock. This can be done by using a hybrid model indicated in Figure 2, quadrant Q3 and Q4. This gives us a starting point for addressing sustainable retrofit actions. The Q4 quadrant enables us to generate white box models which can later be used for a Q3 quadrant black box machine learning model. There are two approaches for generating building energy data. We can either use existing building models. Enova had in 2018 registered 1 111 467 residential buildings with the energy certification "Energimerkeordningen". Of these 134 767 (12%) where simulated by computer programs, mainly Simien. The simulated models represent 5% of the total residential buildings. In addition, the simulated models are generated based on a standardized energy model, which does not take into account realistic data such as local climate and operation. The generated models only output results which gives us less control and validation. This is therefore not recommended for use directly in a white-box model.

Another approach is to generate simplified energy models from scratch which represent most of the building stock. This can be done by parametric simulation where different key performance indicators form chapter 3.2.1 are implemented. It is suggested to outline and study the most important factors before generating the overall models, this should be input parameters which is available from the statistical data model. If we were to use SSB this could be different climate regions, size and age for instance. **Error! Reference source not found.** illustrates a simplified parametric model which consist of size, height and window to wall ratio. The generated data is created with the computer program Rhinoceros 6, using Visual programming and the plug-in ladybug tools and Colibri.

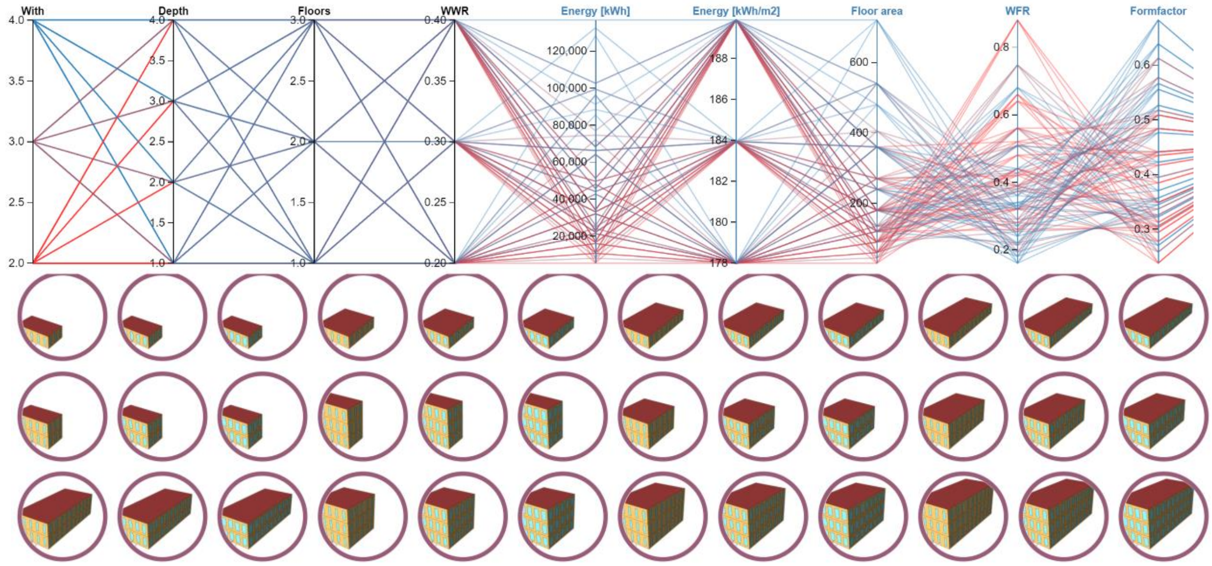


Figure 12 Example of parametric run of simplified energy models for use in a large-scale model.

There are also possibilities to integrate the white-box model in an Artificial neural network for generating even more data. Since the parametric run are time-consuming this could be an efficient way to produce more data to train with for the Q3 model.

With enough consistent and reliable energy data, we can implement the data model in a machine learning algorithm using a neural network. By using supervised learning method with backpropagation, we can train the model to recognize key performance indicators which is established in the parametric model. The method can automatically detect data patterns in order to predict future data.

5 Conclusion

The energy performance of the existing buildings is an important factor for reaching low carbon emissions targets. It is therefore important to have reliable dataset on performance of the currently existing building stocks, based on which we can choose and implement sustainable strategies for future plans. This study investigated how to gather or generate a large-scale energy data of the Norwegian residential buildings. A qualitative literature survey on the existing methods for generating large-scale energy data in buildings was conducted and the followings were concluded:

- A common classification scheme includes a top-down and bottom-up approach. The top-down approach treats the building sector as an energy sink with focus on macroeconomic indicators and is not concerned with individual end-uses. The bottom-up approach estimates energy consumption of a representative set of individual buildings to regional and national sectors.
- Energy modelling techniques can be set into four quadrants based on their design (top-down/bottom up) and degree of transparency (black-box/white-box). In general, the most common modelling approach is physics-based simulations using the bottom-up and white-box modelling. There has been a growing usage of hybrid models with combination of white- and black-box modelling.
- Reliable large-scale energy data can be gathered from existing building data from institutes such as EU Building Stock Observatory and Intelligent Energy Europe. The potential has not been fully utilized and can have great impact combined with energy modelling.
- It is important to be able to visualize the large-scale energy data, since it can be difficult to comprehend, especially for non-technical end-users.

Recommendation: A hybrid model combining simulation-based techniques and machine learning algorithms shows promising results. An energy model class enables us to generate white box models, which simulates the physical relationship of processes at the building or end-use level based on key performance indicators. The dataset can then be trained in a machine learning algorithm, which utilize historical information to attribute building energy use to particular end-uses and can predict different scenarios for the Norwegian building stock based on cadastre data and statistical data. The outcome of this study can help to introduce approaches to find the energy saving potentials in Norwegian buildings and present the suitable refurbishment strategies for future planning.

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