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BUILDING A LOW-CARBON, CLIMATE RESILIENT FUTURE: SECURE, CLEAN AND EFFICIENT ENERGY

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1. Definition of energy demand:

Reducing energy demand is considered to be one of the key tools to reduce GHG (greenhouse gas) emissions in the short to medium time period (Sorrel 2015). Despite this fact, the recent trends of the different aspects of energy demand show that the demand-side of the energy system has been neglected in terms of actions to reduce global warming (Creutzig et al. 2018). However, before discussing further the trends of energy demand, both the terms 'energy' and 'energy demand' should be defined precisely. Energy is generally defined as 'ability to do work' and it is a fundamental input to our modern life (Shove, and Walker, 2014). Energy more precisely energy demand is essential for an individual as well as for a society to function and grow where demand for energy refers to the consumption of energy by any kind of human activity (CREDS 2019, 10th October). Although the meaning of energy demand can vary as per the user perspective, but in general, energy demand refers to "any kind of energy use to satisfy individual energy needs for cooking, heating, travelling, etc., in which case, energy products are used as fuel and therefore generate demand for energy purposes" (Bhattacharyya 2011). In other words, energy demand denotes all the uses of energy such as transport fuels, and fuels for heating and cooling, electricity. However, it is noteworthy that energy demand is a derived demand- meaning, energy is not for direct consumption rather it is consumed for ulterior purposes such as for producing goods and services, for mobility, or for deriving comforts from a service (Bhattacharyya and Timilsina 2009). Thus, derived energy demand can reflect both; the amount of energy required in a country which is termed as primary energy demand, and the amount supplied to the consumers which are termed as final energy demand (Bhattacharyya 2011). In the energy community, energy demand is used to refer to the derived demand for energy. Thus, in this report also, we use the word energy demand to explain derive demand for energy.

After the energy crisis in 1970, energy is acknowledged as a 'social need' and meeting energy demand is considered as a social problem (Van Benthem, and Romani, 2009; Shove, and Walker, 2014). Researchers from different backgrounds such as economics, engineering, sociology, anthropology, philosophy take interest in analyzing the 'need' for energy and its possible consequences to the environment. Thus, both socio-economic analysis and techno-economic analysis are done based on various mathematical tools which provide evidence to understand the opportunities and limitations of the energy system. These energy models are often based on the status quo energy demand pattern and supply situations (Pokharel et al. 2012). Thus, the results of these models provide evidence for the policymaker which can then further be used to minimize global warming and optimize human welfare. However, the mathematical energy models are often criticized based on the fact that they do not incorporate various social and economic factors that influence both the demand and supply of energy. As a result, many of the energy models are accused of not being able to project energy demand and supply beyond a narrow planning period (Pokharel et al. 2012). Moreover, most of the existing energy models are considered as black boxes as assumptions and calculation of these models are hard to follow (Openmod 2019, 5th December). Therefore, the objective of this report is to analyze the trends of energy demand and further explains how this trend clarifies the theoretical literature on energy efficiency. Moreover, this study

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discusses the sector-specific transition trends by analyzing the results provided by different energy demand models. This report further contributes to the knowledge pool by doing a focused literature review of the energy demand models and discussing some key issues concerning the demand models. Project SENTINEL reviews two sectors, the building sector, and the transport sector. Thus, the scope of this literature review limits to these two sectors only. However, it is important to note that the energy demand by the industrial and agricultural sectors are as prominent as building and transport sector, but due to time and resource constraints, this project as well as this report, does not cover these two sectors. This report is the first step towards developing the SENTINEL energy transition modelling framework.
This report is organized in four key sections. The first section introduces the concept and definition of energy and energy demand. Section one further discusses the key trends of energy demand. Section two reviews the different methodologies used in the energy demand models to project future energy demand. Then in section three different energy models used in the building and transport sector are reviewed and also, the issues with the energy models in these two sectors are discussed. Lastly, section four talks about key challenges of modelling energy demand and the next step forward in this project.

1.1 Key trends of energy demand:

As per the IEA (2019) report, energy demand globally has increased rapidly over last decade and this increase in demand does not only include demand for conventional energy sources such as natural gas and oil, but demand for renewable sources (for example solar and wind energy) are included as well with a double-digit growth. This high energy demand results in high energy consumption which is almost the double of the average growth rate since 2010 (IEA 2019). As a result of high energy consumption, energy-related CO2 emissions have increased by 1.7% (IEA 2018). Thus, it can be inferred that renewable energy demand although it increases, still could not able to substitute the non-renewable energy sources. Therefore, the importance of the policies on both energy efficiency and renewable energy use are required around the world to curb down energy-related GHG emission. For instance, the new regularity framework of the European Union sets an energy efficiency target of 32.5% and a renewable energy target of 32% for the EU for 2030 (European Commission 2018). However whether these targets would be adequate to restrict the global temperature rise by 1.5 degree, would require forecasting of energy demand by incorporating all the important factors that includes energy price, population growth, urbanization rate, diffusion rate, and many more (Psiloglou et al. 2009; Madlener and Sunak 2011). Forecast of energy demand is important for energy planning and to assess the future energy demand, energy demand models are used (Worrell et al. 2004; Bhattacharyya and Timilsina 2009). The policymakers often rely on the results of energy models to decide on which policy to implement. Craig et al. (2004) study argued that a forecast is considered to be successful if

i. The results or modelling parameters influence the policymakers
ii. The outcome of the forecast has a significant impact on the public opinion and on the opinion of the energy community

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iii. The forecast modelling represents the underlying physical and economic principles of the sector/world or it highlights the key economic or social patterns though the energy model.

However, it is noteworthy that projected demand for energy often deviates from the actual demand due to the limitations of estimation models and their assumptions (Bhattacharyya and Timilsina 2009). There could be several other reasons behind this deviation from the actual energy demand. Perhaps the most interesting reason why a modelling result may vary is that anticipating issues can prompt into maintaining a strategic distance from the issues. In this case, the failure of projection would demonstrate the accomplishment of the model (Craig et al. 2002).

Energy efficiency and energy demand: As discussed in the above section, in 2018, the global energy demand- more precisely global primary energy demand grew by 2.3%. As per IEA (2019) report, this increase in global demand is mostly contributed by the growth of fossil fuels (70%) which outweigh the 24% increase from renewables in primary demand. Figure 1 below shows the pattern of the global primary energy demand of the previous eight years:

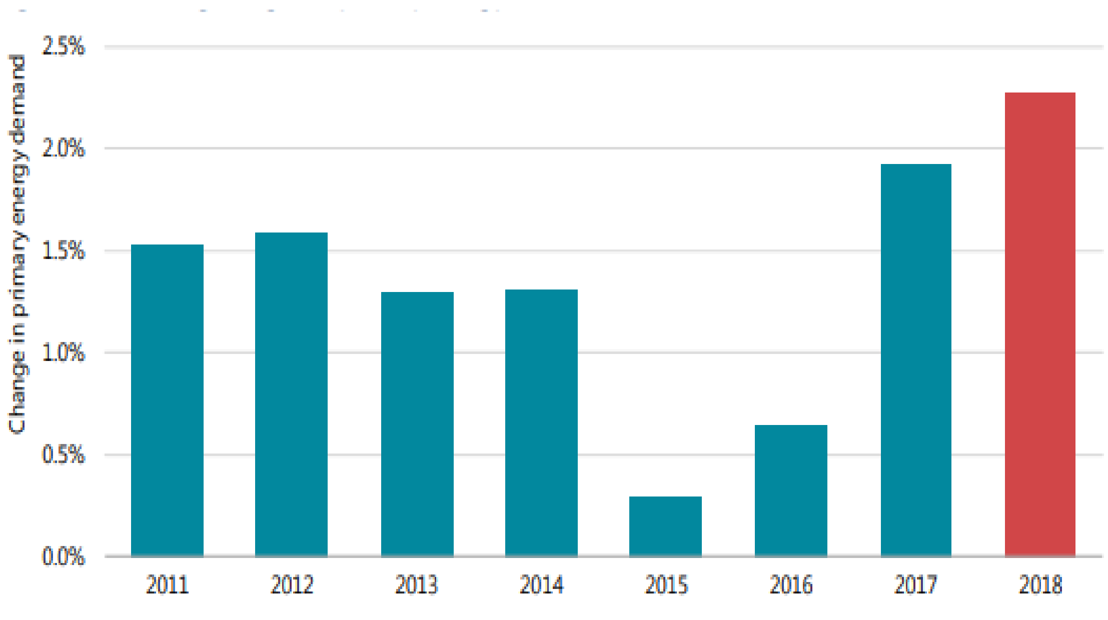

Figure 1: Trend of global primary energy demand

Source: IEA (2019)

Figure 1 clearly shows that the global total primary energy demand increase is the largest since 2010. Moreover, the increase in primary energy demand and the high proportion of fossil fuels in the energy mix have led to an increase in GHG emissions which 'reached a historic high of over 33 billion tonnes of carbon dioxide' (IEA 2019). If we analyze further the rate of increase in primary energy demand, it would be clear that this increase in primary energy demand is mostly led by growth in fossil fuel production. More precisely, 70% of the primary demand is accounted by fossil fuels growth. Within the total growth of 70%, natural gas accounts for 46%, oil 15%, and coal 9%

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which together outweigh the growth from renewables (24%) in primary demand (IEA 2019). Therefore, the role of efficiency improvement which would reduce the energy demand has become crucial. Reducing energy demand through improved energy efficiency where energy efficiency is defined as "using less energy to produce the same amount of services or useful output" (Patterson 1996), is the cheapest, and fastest means to mitigate climate change (Sorrell 2015). Thus, by definition, improvement in energy efficiency would reduce the demand for energy for a particular service. However, in practice, the improvement in energy efficiency may not always result in less demand for energy or the demand reduction may occur due to some other reasons which have nothing to do with efficiency improvement. Hence, it is always recommended to specify the reference against which those energy savings or demand-reductions are measured or estimated by specifying the appropriate spatial and temporal boundary, assumptions and measuring unit (Sorrell 2015).

Generally, in energy policy analysis, the improvement in energy efficiency is measured by energy intensity where energy intensity is defined as "the ratio of energy consumption to GDP" (Filippini, and Hunt 2011). More precisely, energy intensity reflects the amount of energy used for per unit of activity. Hence, to understand the impacts of different energy efficiency measures in different sectors such as building, transport, industry, it is recommended to examine the final energy demand instead of primary energy demand. As per the Energy Outlook Report (2019), the global final energy demand has also increased by 2.2% in 2018 which is similar to global primary energy demand. Figure 2 below shows the trend of global final energy demand by different fuel sources:

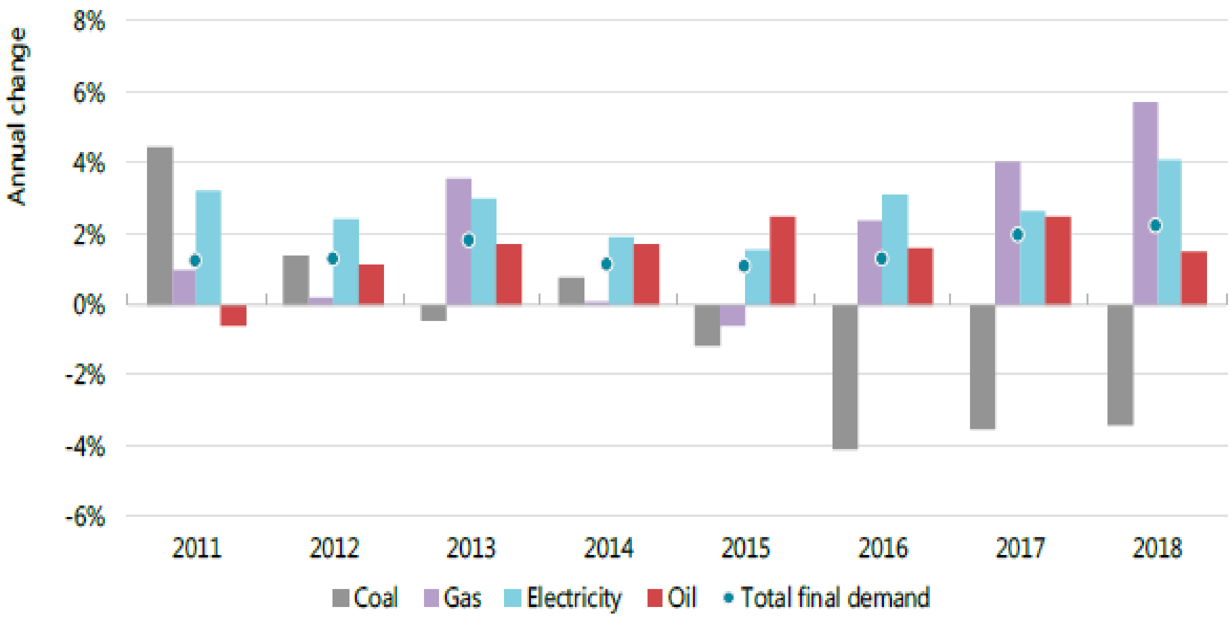

Figure 2: Change in global final energy demand by different fuel-types

Source: IEA, energy outlook report 2019

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Figure 2 decomposes the percentage change of different fuel types over the past eight years. From this figure, it is clear that the demand for coal has been consistently declining from 2013 and the rate of declining demand for coal ranges from 0-4% over the past eight years. Although there is a declining trend for coal, the final energy demand shows an upward trend. One of the key reasons behind increasing final demand is growth in natural gas (5.7%) and electricity (4.1%). In other words, the demand for coal has shifted to gas and electricity mostly demanded for heating, cooling, and use of appliances. Moreover, oil accounts for around 41% of the final global demand which is the largest share of the final demand. However, the rate of increase in oil demand has slowed in 2018 compared to 2015 due to the high price of oil. Thus, the transport sector also looking for alternatives to oil and has switched some part of the demand for natural gas and other active modes of travel.

The demand for renewable energy although increases but still electricity generation from different renewable sources such as wind, and solar photovoltaics (PV) supply varies as per the location and time. Thus, these renewable energy sources are called variable renewable energy sources (VRES) (Ringkjøb et al. 2018). Both the solar and wind are difficult to predict and hence, unable to provide the required grid support services which include 'frequency and voltage regulation, fault ride through, spinning reserve and system restoration' to keep up a steady and reliable grid which are fundamental to the energy systems (Boßmann and Staffell 2015; Ringkjøb et al. 2018). The cost of renewable energy has decreased significantly and now they are inexpensive compare to conventional fossil-fuel based energy generation (Staffell, and Pfenninger 2018). Due to the ongoing technological improvement in renewable energy-based electricity generation, both wind and solar capacity globally have increased to 790 GW in 2016 from 80 GW in 2006 (Staffell, and Pfenninger 2018). This also implies that the power systems are becoming more and more dependent on the weather conditions. Therefore, to better understand this impact and strength of VRES run electricity generation, the energy models can play a crucial role.

Here, it is important to discuss that there exists a distinction between energy demand and energy consumption. Energy demand shows the relationship between price/wealth, income, and quantity demanded of energy for the energy carrier or quantity demanded of energy for the final energy use (Bhattacharyya 2011). Hence, energy demand exists before the purchasing choice is made that means it is an ex- ante concept. Whereas energy consumption takes place once the purchase decision is made- in other words, once energy demanded and purchased then only consumption of energy starts (Bhattacharyya 2011). Thus, energy consumption is an ex-post concept. However, in energy policy analysis, energy consumption and energy demand are often used interchangeably.

2. Overview of modelling methods:

The energy demand models can be categorized in many ways, while there is rarely any model that can fit into one distinct category. Grubb et al (1993) study categorize energy models with the help of six dimensions which are applicable for energy demand models as well. The six dimensions are- 1) top-down and bottom-up approaches, 2) time horizon, 3) sectoral coverages, 4) optimization and simulation techniques, 5) scale of aggregation and 6) geographical coverages. These classifications of energy models are not an exhaustive list as there could be other dimensions/categories, for instance, hybrid models, and backcasting models. However, the energy demand models mostly

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follow two approaches which are top-down and bottom-up approaches. These two model categories mainly differ due to the technological details of the energy and also due to the comprehensiveness of endogenous market adjustments (Böhringer and Rutherford 2008). Moreover, both top-down and bottom-up models can be further subdivided into two more categories. For instance, the models using a top-down approach can be further categorized into econometric and technological models whereas the models using the bottom-up approach can be categorized further into statistical and engineering models (Swan and Ugursal, 2009). These categorizations of models are done to understand the differences and similarities of different energy models. This categorization or classification of models can facilitate the selection of the proper energy models (Van Beeck 2000). However, the use of the model is determined by three key drivers namely 1) purpose of the research, 2) external or input assumptions, and 3) structure of the model (Van Beeck 2000). Thus, different energy models are used for different end-use sectors. Usually, energy demand is divided by energy consumptions of different sectors and the sectors often coincide with the economic sectors such as Industrial, residential, tertiary and transport sectors, of a country (Paez et al. 2017). In addition to these sectors, other consumption sectors for example, mining or agricultural sector also consume energy (BP, 2016; Paez et al. 2017).
Behind every energy model, there are three methodologies used to project energy demand. These three methodologies are 1) simulation methodology, 2) optimisation methodology, and 3) equilibrium methodology (Ringkjøb et al. 2018). Each of these methods is described in the section below:

2.1. Simulation methodology:

Simulation models simulate a component of energy-system (such as energy demand) or the whole energy system based on certain specified equations and characteristics (Ringkjøb et al. 2018). Simulation methodology generally uses a bottom-up approach, since the simulation of a component of the energy system or stimulation of a whole energy system requires a detailed technological description of the system. Thus, every simulation methodology contains an equation or a set of equations that represent the behavior of the component of energy system or the whole system. Moreover, simulation models can also test various system topologies and their impacts from various scenarios (Ringkjøb et al. 2018). For example, agent-based modelling in the transport sector often uses simulation methods to analyses the energy demand of the transport sector.

2.2 Optimisation methodology:

Optimization models are used to optimize a specific component of the energy system among a set of alternatives by minimizing or maximizing the component considering the given inputs and also by meeting the given constraints. Generally, energy investment decisions are suggested/taken by using optimization models. Optimization models mostly use three techniques namely; 1) linear Programming (LP), 2) non-linear Programming (NLP), and 3) mixed Integer Linear Programming (MILP) techniques (Neshat et al. 2014). The type of technique is determined based on the research question the model is exploring and by the data availability. For instance, to explore the amount of investment in renewable energy to meet the energy demand, one needs to use the MILP technique. However, as Ringkjøb et al. (2018) study argued that "the majority of optimization models use a linear programming (LP) approach, with an

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objective function which is either maximized or minimized (e.g. minimizing the total system cost), subject to a set of constraints (e.g. balancing the supply and demand in the grid)".

2.3 Equilibrium methodology: Equilibrium models use an economic approach where energy demand is modelled as a part of the whole economy and further it analyses the impact of energy demand on the rest of the economy. Popular models such as General equilibrium models, or computable general equilibrium models (CGE), use equilibrium methodology. These models consider the economy as a whole and then determine important economic parameters such as the gross domestic product (GDP) endogenously as a change of energy demand (Ringkjøb et al. 2018).

Figure 3 below presents different methods used by the energy models.

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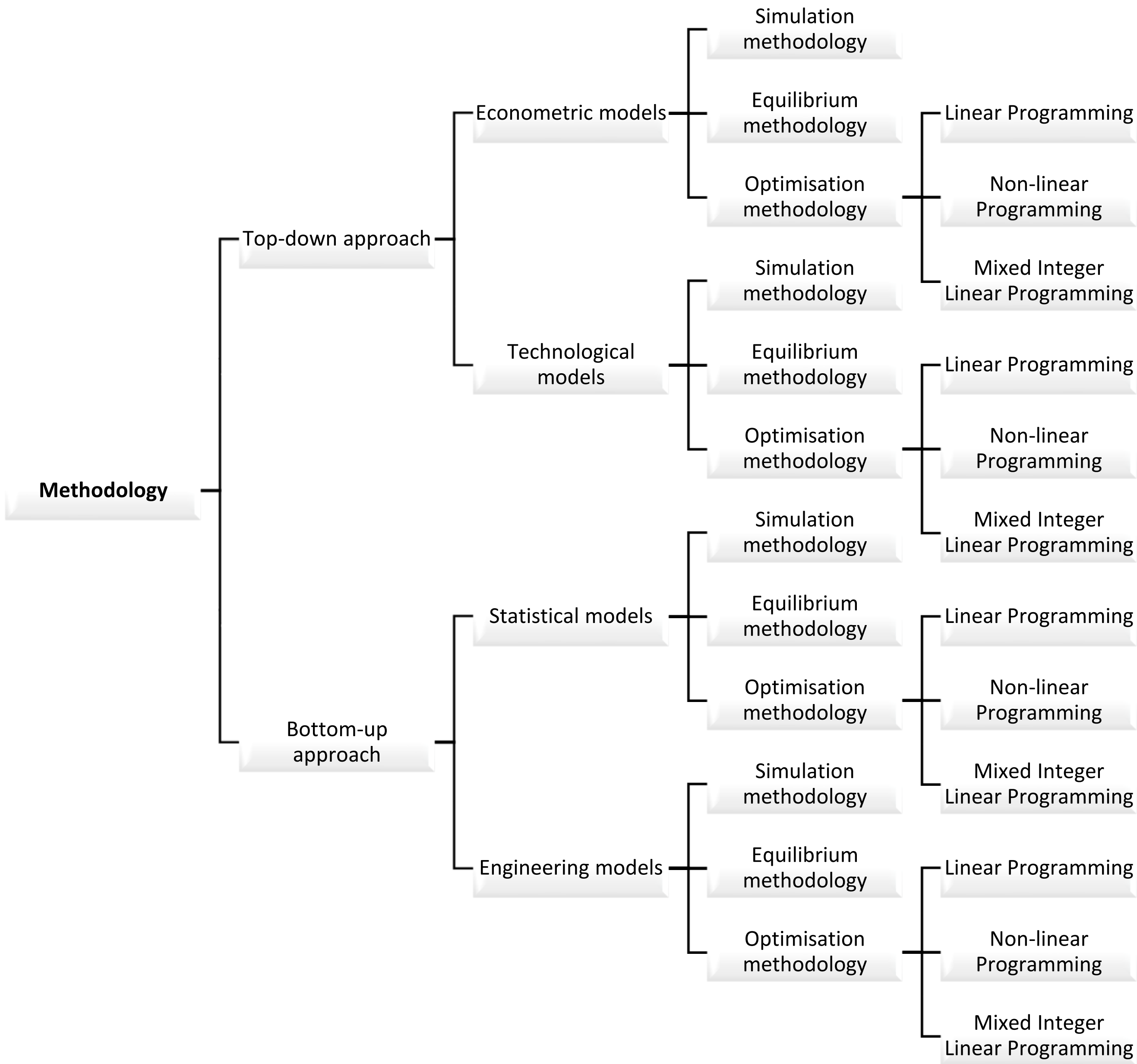

Figure 3: Flowchart of methods used in energy models

Source: Own elaboration

Different methodologies are used in different categories of models. Also, the methodology of energy models depends on the type of research question the model wants to answer. For instance, any to answer investment or cost-related problems in the energy sector would be answered by using simulation methodology. In case, a researcher wants to see the overall impact of various energy policies on the economy, then equilibrium models would be used- for example, Computable General Equilibrium (CGE) models use equilibrium methodology in order to evaluate a whole impact on the

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economy. More examples of different models using different methodologies are discussed in table 1 and table 2.

3. Types of energy models:

Different categories of models and different methodologies used by these models often vary both across and within the end-use sector. The usage of the model is determined by the research question and also by the availability of input data. In the section below, some of the sector-specific energy demand models are discussed to explore the diversity of different energy demand models. The objective of this section is not to review every single energy demand model for the building and transport sector, but rather the objective of this review is to provide an understanding of some of the key energy demand models of these two sectors. Also, a review of all the existing energy demand models is difficult as models are continuously being developed and updated. Further, this study does not review any system models (such as MARKET, TIMES, MESSAGE, PRIME, etc.) as they will be discussed in the SENTINEL WP 4 report. However, some of the specific branches of system models are included in the review to provide a clear picture of energy demand.
To gather information about sector-specific demand models, we have done a thorough literature review and also at the same time, we have circulated a 'call for evidence' among the energy community to collect information about both published and unpublished (grey literature) models. Considering both the time and resource constraint, circulating a 'call for evidence' along with a rigorous literature review seem to be the best option.

3.1 Building sector:

Globally building sector consumes one-third of all end-use energy (Isaac and Van Vuuren 2009). In other words, as cited in Urge-Vortsatz et al. (2015), the building sector- more precisely residential and commercial building sector contributed 24% and 6% respectively of global final energy demand (32% in total by the building sector) in the year 2010 which accounts 30% of energy-related CO2 emissions globally. Literature (such as- Abergel et al. 2017; Urge-Vortsatz et al. 2015; Levine et al. 2007) documents that energy consumption of the building sector has been growing and without any policy intervention, it is expected to grow rapidly over coming years. The key reasons behind the growth of energy consumption include population growth, economic growth as it would also imply improved access to electricity, higher usage of space cooling, and higher use of electrical appliances (Lucon et al., 2014; Rogelj et al. 2018). If this trend continues, then energy consumption is likely to increase by 50% in 2050 compared to 2010 energy consumption level (Rogelj et al. 2018). However, if sector-specific efficiency measures are taken then a declining trend in 2050 compared to the 2010 level can be achieved (Rogelj et al 2018). The are several ways to achieve this declining trend such as 1) controlling energy demand, and 2) electrification of the building sector (Rogelj et al 2018; Knobloch et al. 2019). In order to reduce the energy demand of the building sector, different energy efficiency measures designed for the building sector have a vital role to play. For instance, 56% of the final energy is used for heating which includes both water and space heating, in the residential building sector. Among this 56% of energy demand for heating, 55% of energy is generated from fossil fuels (Knobloch et al. 2019). Therefore, it can be concluded that heating and cooling demand

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has the highest energy saving and GHG emission reduction potential which can be utilized by implementing different energy efficiency measures along with renewable equipment to achieve 1.5-degree temperature (Lucon et al. 2014; Rogelj et al. 2018; Knobloch et al. 2019). Although these studies clearly show that space heating and cooling dominates the energy demand but, however, a recent data projection indicates a shift towards space cooling and appliance usage-related demand. In other words, a recent projection done by Levesque et al. (2018) study indicate that space cooling, and appliances would dominate building energy demand in the future.

Further, energy intensity in the building sector continues to improve by 1.5% per annum where energy intensity represents energy use in the building sector per m2 (Abergel et al. 2017). Simultaneously with the improvement in energy intensity, the global floor area also continues to grow with about 2.3% rate annually (Abergel et al. 2017). Thus, the growth floor area outweighs the effects of improvement of energy intensity and as a result, emission from the building sector globally and construction (of the buildings) sector continues to grow. In figure 4 below the global building sector's energy consumption by type is presented to elaborate this above point further:

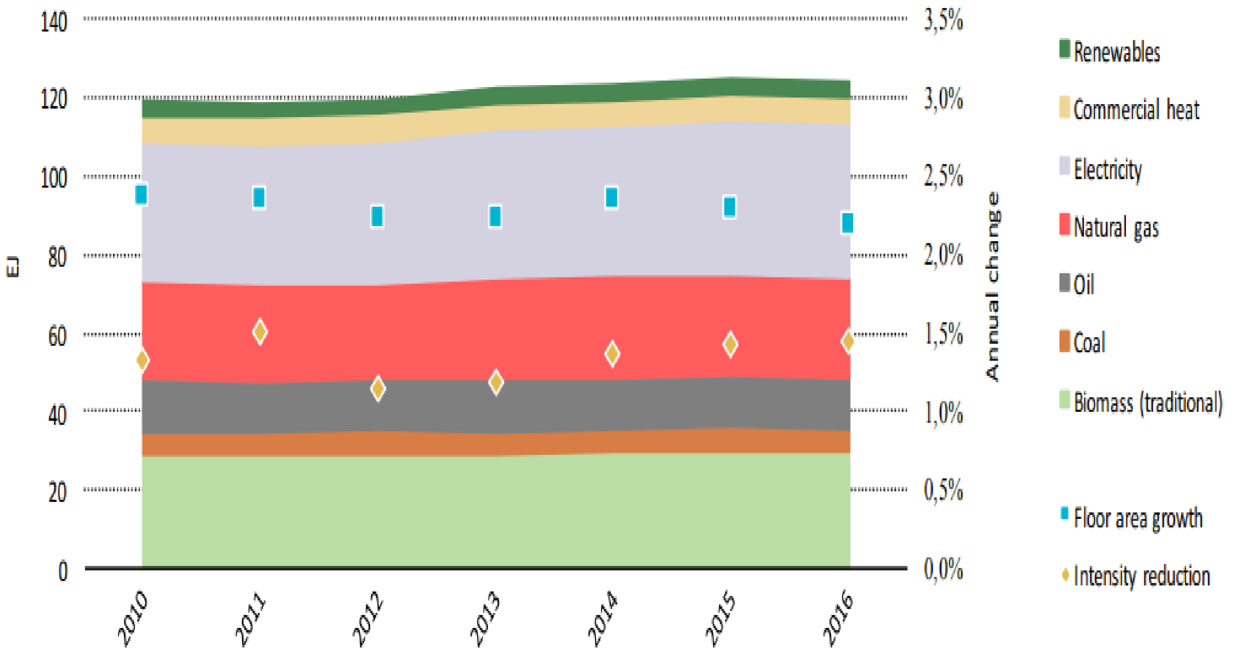

Figure 4: Global buildings sector energy consumption by fuel type, 2010 – 2016

Source: (Abergel et al. 2017)

Figure 4 decomposes the different types of energy used by the building sector. From this figure, it can be clearly seen that the most used form of energy is electricity followed by natural gas and biomass. Energy demand and its consumption vary depending on the sectors which include the residential building sector and commercial building sector. Globally, the major share of the energy is demanded for thermal uses- for instance, over 60% and almost 50% energy are demanded for thermal uses by the residential and commercial building sector respectively (Ürge-Vorsatz et al.

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2015). However, to keep the global warming by 2-degree target, 32 Gt of CO2 emissions reduction is required between 2010 and 2050 from the building sector globally, and in order to keep the warming below 1.5 degrees, further 28 Gt of decrease would be essential by the global building sector (Wang et al. 2018). Thus, the mitigation potential of both residential and commercial building is required to be utilized in order to attain the 1.5-degree target. Therefore, new state-of-the-art building concepts such as nearly zero energy buildings, passive houses, are required where on-site renewable energy systems (such as PV, wind turbines, or solar thermal) are present which can generate as much energy as is consumed by the building over one year (Lucon et al. 2014). One example of such implementation of zero energy buildings can be seen in the European Union where European Commission Recommendation (EU) 2016/1318 of 29 July 2016 recommends that by 2020, all new buildings within the EU should be nearly zero-energy buildings[1]. The impact and cost implication of implementing these kinds of policies need to be understood precisely in order to design and implement such visionary policies. Thus, energy demand models that also include cost implications could play a vital role to formulate such visionary polices.

In the section below, some of the building sector specific energy demand models are discussed to explore the diversity of different energy demand models. The objective of this section is not to review every single energy demand model of the building sector, but rather the objective of this review is to provide an understanding of some of the key energy demand models of the building sector and modelling trends of this sector. Also, a review of all the existing building-sector energy demand models is difficult as new models are ceaselessly being developed almost every other day and old models are being updated quite frequently.

Table 1: List of energy demand models for the building sector

[1] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32016H1318

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Model name	**Host institution**	**Time span**	**Geographic coverage**	**Modelling method/approach**	**Description of the model (some key assumption, a brief description of the model, specific end-use analyzed)**	**Key drivers**	**License (Open/close)**	**Key relevant papers/reports**
Wuppertal	Wuppertal Institute	2005-2020	EU 25 member states	Wuppertal model uses a technology-oriented bottom-up approach.	This model estimates GHG emission for building sector based on both the final and primary energy demand. This model uses a scenario analysis where different policies and measures (which includes market penetration of renewable energies, CFL installation, improvement of HVAC system, energy efficient appliances) are considered as an efficient scenario along with a business-as-usual scenario. Moreover, in this model the measures and policies to mitigate GHG has been selected based on their cost-efficiency potential at the national level.	-Economic Parameters - Time period for pay back - Energy demand (both final energy and primary Energy)	Unknown	Lechtenböhmer et al. 2005

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INVERT/EE-Lab	Vienna University of Technology /EEG	2030/2050/2080	EU 28 member states	INVERT/EE-Lab model uses a dynamic bottom-up techno-socio-economic simulation methodology. Moreover, this model uses Python codes to execute the methodology.	This model assesses the impacts of various policy bundles aiming at the total energy demand, energy carrier mix, CO_2 reductions along with expenses for space heating, cooling, hot water and lighting demand in buildings. This model is specifically equipped to evaluate the future energy demand for space heating and cooling in the EU 28 countries.	-Building stock -Space heating and hot water technologies -Energy prices -Component based U values	Closed	Fleiter, T. et al. (2016) https://invert.at/index.php
The Built Environment Analysis Model (BEAM2)	Ecofys	2012-2050	Global	BEAM2 is a calculation model that computes a set of data, which includes parameters such as energy consumption, CO_2 emissions, costs due to installation of energy efficiency measures and energy supply	The Built Environment Analysis Model (BEAM2) shows the impacts of different policy scenarios on energy demand, and GHG emissions for the building sector. More precisely, BEAM2 provides a comprehensive detail of energy demand, GHG emission, and cost for space heating and cooling, hot water and auxiliary energy in buildings. This model is a calculation model which can	-Energy price - Interest rate - Building stock - Climate zones - Investment costs for insulation and Building equipment	closed	Boermans, T., Bettgenhäuser, K., Offermann, M., & Schimschar, S. (2012)

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				systems of buildings	be applied for any building stock globally.	- Energy consumption data for heating, cooling, hot water and auxiliary energy		
Future Technology Transformations' (FTT: Heat) model	Radboud University	2050	59 regions in the world which includes regions from EU member states	FTT: Heat model uses a non-equilibrium bottom-up simulation	This model aims to predict the composition of different technologies of the heating systems of the residential sector in 59 regions globally including the EU member states. Further, this model project technological composition under some assumptions on heat demand and choice behavior. Moreover, FTT: Heat model projects the fossil fuel used and CO_2 emission by stimulating various sets of possible policy strategies. FTT:Heat is an integrated model (in collaboration with the global macro-econometric model E3ME). E3ME can	- Macroeconomic indicators (such as household income, GDP ,employment) - Investment costs, fuel cost - Technology diffusion rate	Unknown	Knobloch, et al (2017); Knobloch et al. (2019)

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					project the multiplier effects and macro-economic effects of residential heating demand.	-Lifetime of a technology		
The Behavioral change in energy consumption of Household (BENCH) model	University of Twente	2020/2030	Selected EU regions	BENCH is an agent-based model which uses simulation technique to estimate behavioral effects on energy demand	BENCH model stimulates behavior which are complex and nonlinear, and also that is obstinate in equilibrium models. By tracking behavior, BENCH evaluates the aggregated impacts on energy demand by heterogeneous households.	-Annual income of the household -Electricity consumption -Energy label of a dwelling -Dwelling tenure status -Psychological factors	Unknown	Niamir, Leila, et al. 2018
The Bottom–Up Energy Analysis System (BUENAS) model	Lawrence Berkeley National Laboratory	2005-2030	Nine regions across the globe including EU	BUENAS model uses bottom-up approach and simulation technique to project energy demand of the household.	The Bottom–Up Energy Analysis System (BUENAS) is a bottom–up stock accounting model which predicts energy consumption for each type of equipment (appliances, lighting, and HVAC) by using an engineering-based estimation	-GDP -Building stock -Urbanization -Population	Unknown	McNeil et al. 2013

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					method of annual unit energy consumption. Energy demand for each scenario is derived by data on equipment stock, usage, efficiency, and intensity.			
TIMER-Residential Energy Model: Global (TIMER-REMG)	PBL Netherlands Envrionmental Assessment Agency	Global, 26 regions	1971-2100	TIMER-REMG is a part of an integrated assessment model (IMAGE). It uses recursive dynamic technique. Moreover, this model uses M modelling a numeric modelling tool to execute its calculations.	TIMER-REMG model builds on building stocks and their demand on energy based on relationships between energy demand and economic growth. Different fuels/technologies/efficiency investments compete for market shares of the energy demand based on their relative costs, including fuel and capital costs. Energy demand services: space heating, space cooling, water heating, lighting, cooking, and appliances. Each of the above services can be met from 8 energy carriers: coal, oil, natural gas, modern biofuels, traditional biofuels, secondary heat, hydrogen, electricity (appliances can only be met	- Households income - Floor space - Appliance ownership - Discount rates -Energy prices -Regional climatic characteristics -Insulation investment costs -Capital costs for efficient	Closed	Daioglou et al. (2012)

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					with electricity, secondary heat can only provide space and water heating).	heating devices		
TIMER-Services	PBL Netherlands Envrionmental Assessment Agency	Global, 26 regions	1971-2100	TIMER-Services is part of an integrated assessment model (IMAGE). Projections based on relationships between energy demand and economic growth. Different fuels/technologies/ efficiency investments compete for market shares of the energy demand based on their relative costs, including fuel and capital costs. Calculation process is recursive dynamic. Moreover, this	Energy demand services: Space heating and cooling, water heating, lighting, cooking, and appliances. Each of the above services can be met from 8 energy carriers: coal, oil, natural gas, modern biofuels, traditional biofuels, secondary heat, hydrogen, electricity (appliances can only be met with electricity, secondary heat can only provide space and water heating). Space heating and cooling depend on regional climate conditions. Investments in insulation (6 insulation levels) reduce heating/cooling demand.	- Value added from services -Energy prices -Regional climatic characteristics -Insulation investment costs -Capital costs for efficient heating devices	closed	Fleischmann Napadenschi, J. (2015)

				model uses M modelling a numeric modelling tool to execute its calculations.				
High efficiency Building (HEB) model	CEU	11 regions including EU 27 and selected countries, such as China, US and India	2005-2050	HEB model uses a bottom- up approach to calculate the energy performance of the buildings irrespective of the measures taken to accomplish it.	HEB model analyses building energy use and CO2 emissions. Tis model uses a systemic perspective which is the performance of the whole system (e.g. whole buildings) and these performance values are used as inputs in the scenarios. Moreover, this model captures the diversity of solutions required in each region by having region-specific assumptions about advanced and sub-optimal technology mixes.	-Population -GDP -Energy Use -Technological -Development -Building stock	Closed	Guneralp et al. (2017) Urge-Vorsatz, D. et al. (2012)
Building integrated solar energy (BISE) Model	Ksenia Petrichenko	11 regions across the globe	2005-2050	BISE model uses a bottom-up approach with geospatial analysis.	This model combines energy modelling by incorporating energy use by the building and on-site solar energy production with geospatial analysis, using a number of geographic information systems (GIS). The	-Building stock - Top of atmosphere irradiation, -Global irradiation,	Closed	Petrichenko, K. (2015)

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					main objective of this model is to ascertain the highest possible technical potential of solar energy which is integrated in the building to meet energy needs of the building.	-Ambient temperature, -Wind speed		
Energy Demand Generator (EDGE) model	PIK	Global	2010-2100	The EDGE model does both short-term and long-term projection based on different scenarios.	EDGE model projection follows four steps: 1) firstly, it collects historical data and then based on that, scenario projections of the energy demand in the buildings sector are made. 2) It calculates useful energy demand and also the floor space. 3) EDGE model estimates the future changes in final-to-useful energy efficiencies as well as energy carrier shares for each end-use. 4) Lastly, final energy demand is computed for the building sector.	-Population -Population density -per capita income - Heating and Cooling Degree Days -Floor space demand	Unknown	Levesque et al. (2018)
Demand for Energy Services, Supply and Transmission in EuropE (DESSTINEE) moel	Bossmann & Staffell	Europe at country-level	2050	DESSTINEE model uses stimulation method to explore future energy system transition	The DESSTINEE model is intended to test presumptions about the technical prerequisites for energy transport (particularly for	-Population -Economic growth	Open	Staffell, I. L., & Bossmann, T. (2015)

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				pathways for Europe.	electricity), and the associated challenges to build up the fundamental framework. DEESTINEE consists of three modules: a scenario generator, a demand profile builder, and an electricity market simulator.	- Fuel and carbon prices - Efficiency improvement - Heating & Cooling thresholds		
Dynamic high-Resolution dEmand-sidE Management (DREEM) model	TEESlab UPRC	1. Regional 2. National (after upscale)	User-defined (e.g., 2015 - 2030, or 2020 - 2050)	DREEM model is a hybrid bottom up model which fills in as a passage point in Demand-Side Management displaying in the building sector. DREEM model uses Python 3, Modelica to construct its modelling platform.	DREEM model is decomposed into many individual modules namely "the interdependence of decisions within modules; the independence of decisions between modules; and the hierarchical dependence of modules on components embodying standards and design rules" (Stavrakas and Flamos 2020). This particular methodology takes into consideration greater adaptability regarding conceivable framework arrangements and computational proficiency towards a wide scope of situations concentrating	-Weather data -Climate Zones -Building specifications -Activity profiles -Appliances data -Thermal comfort parameters -Competitive electricity -HVAC, PV & storage	closed	Stavrakas and Flamos (2020)

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					various parts of end-use It likewise gives the capacity to fuse future innovative achievements in detailed manner.	installations, smart-Thermostat		
Invert/Accounting	TU Wien	32 European Countries	2010-2055 (2080)	The Invert/Accounting model builds on the Invert/EE-lab model and it is a dynamic simulation model that calculates the energy demand and supply, costs and emissions for heating and cooling of buildings based on technical building properties using archetype buildings. It uses Python to derive the model outcomes.	The Invert/Accounting model evaluates the effects of different exogenously defined retrofitting measures and retrofitting rates on the total energy demand, energy carrier mix, CO2 reductions and costs for space heating, cooling, hot water preparation and lighting in buildings. It provides a detailed view on energy demand, GHG emission, and cost for space heating and cooling, hot water and auxiliary energy in buildings.	-Building stock - Climate zones - Predefined retrofitting measures and retrofitting rates	Closed	Fritz (2016). Steinbach (2016) Müller (2015)

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Invert/Opt	TU Wien	32 European Countries	2010-2055 (2080)	The Invert/Opt model builds on the Invert/EE-lab model. It is an optimization model as well that calculates the least cost building stock transformation for a given point in time under restrictions such as CO2- target emissions, availability of energy carriers in different regions and building types and/or shares of heated building areas per energy carriers.	The Invert/Opt model derives the least cost building stock configuration under consideration of the existing building stock, technoeconomic transformation costs (costs of retrofitting measures), energy prices, availability of energy carriers, upper and lower boundaries on retrofitting rates and upper and lower boundaries on the share of heated area per energy carrier. From the results detailed insights on the total energy demand, energy carrier mix, CO2 reductions and costs for space heating, cooling, hot water preparation in buildings can be gained. Due to its focus on heating and the underlying demand calculations it is recommend that to apply it to regions with similar climate and housing structures as are found in Europe.	Building stock - Climate zones - price and cost data - availability of energy carriers - targets for CO2-emission reduction, shares of energy carriers	Closed	Fritz (2016). Steinbach (2016) Müller (2015)

Source: Own elaboration

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Table 1 shows some of the key building-sector related energy demand models and from this review, it is clear that the majority of these models focuses on specific end-use functions of the building sector such as space heating and cooling, lighting, water heating, and appliances. Analyzing these end-use functions requires detail micro-level information, and hence, most of the models reviewed in table 1 use bottom-up approach to analyze the energy demand of the building sector. Another key reason behind using bottom-up approach is that this approach identifies the most feasible options among the best available technologies and processes for carbon reduction targets (Rivers and Jaccard, 2005).

Further, the models reviewed in this study, have mostly estimated their predictions of energy demand and CO_2 emission based on different scenarios to incorporate certain changes such as policy intervention or technological improvement. These changes are then compared with a reference baseline which shows no significant changes. This way the effect of a policy intervention or a technological improvement can be calculated as "a difference between the reference baseline and the scenario with technological changes" (Urge-Vorstaz et al. 2012). For instance, the Wuppertal model considers two scenarios- more precisely one 'efficient' scenario that considers implementation of different energy efficiency measures, which is compared with a business- as usual (status quo) scenario. The efficient scenario in every model essentially comprehends various strategies to mitigate CO_2 emission. The common strategies that are incorporated in the efficient scenario are as follows:

- Retrofitting building envelope which includes higher insulation of walls, roofs, slabs, and ceilings
- More energy-efficient HVAC systems
- More efficient water heating systems
- More energy-efficient appliances
- Integration of renewable energy
- Energy-efficient lighting
- Carbon taxing
- Behavioral changes

With the help of these various strategies, the final outcome of the models analyzed are mostly two - 1) energy consumption/energy demand, and 2) CO_2 emission.

The majority of the energy demand models take the above-mentioned mitigation options to build their scenarios and accordingly they project energy demand under different scenarios. For instance, both HEB and BUENAS model project final energy demand globally to be reduced by 50% and 37% respectively by 2030 under 'efficiency scenario' compared to their baseline (Urge-Vorstaz et al. 2012). Similarly, Economidou et al. (2018) study use Invert/EE-Lab model to analyze energy consumption by the building sector of Cyprus. This study has found that the final energy consumption which includes energy consumption for cooling, heating, hot water, and lighting, in Cyprus is likely to decrease up to 16% in 2050 compared to the baseline scenario. In these models efficiency scenario assumes most ambitious mitigation options/ policies compared to their baseline scenarios and the final energy demand is derived from energy demand of end-use functions such as demand for space heating and cooling, and demand for water heating. Some studies (see Roberts, 2008; Madlener, & Sunak, 2011; Levesque et al. 2018) argue that due to population growth and

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hence, increase in the floor area, the energy demand for heating and cooling, and appliance will increase rapidly in future under the status-quo scenario. However, Urge-Vortsaz et al. (2012) study show that despite the increase in the floor area (approximately 127% increase in the floor area globally) the demand for water heating, and space heating and cooling can be reduced up to 29% and 34% respectively by 2050 if ambitious climate policies are taken. Here, it is important to note that these efficiency scenarios used by the HEB model, Invert/EE-Lab model or by BUENAS model do not incorporate the integration of renewable energy sources and also they do not incorporate the behavioral changes as well. Niamir et al. (2018) study show by using the BENCH model that the behavioral change alone can save up to 20-36% of energy by 2030 in the Navarre region of Spain. This shows the potentiality of behavioral change to obtain energy savings. Thus, demand models should incorporate behavioral change in their efficiency scenario. In contrary to the efficiency scenario results and incorporation of ambitious climate policies, Levesque et al. (2018) study project final energy demand by using EDGE model which shows that without any further climate change policies, the final energy demand of the building sector could increase up to 226% globally by 2100. Similar to the above-mentioned studies, this study also derived final energy demand by incorporating demand of appliance usage along with space heating and cooling. Moreover, it is important to note that historically energy demand is not stable across the year. Seasonal variability is another crucial factor that determines energy demand of the building sector. For instance, Staffell and Pfenninger (2018) study use DESSTINEE model to show that Britain's energy demand increases by 24% in January (mean January demand) in 2030 compare to the 2015 level, while demand in summer remains almost unchanged. This rise in demand in winter is caused by the projected increase in the residential heat pumps. However, on the positive side, it is projected in the Staffell and Pfenninger (2018) study that by 2030 almost 44% of Britain's net energy demand can be met by renewable energy sources. The use of renewables would although make the energy system less carbon-intensive, but it makes the energy system more weather dependent, and hence, seasonal weather profile would emerge as an important factor in the future that also determines the gross demand for energy.

Globally around 35% of the CO_2 emissions from the buildings sector come straightforwardly from the buildings themselves in the form of direct energy-related CO2 emissions, and 65% of the emission comes indirectly from the power sector through consumption of electricity as the electricity-related indirect CO_2 emissions (Urge-Vorstaz et al. 2012). Hence, to reduce CO_2 emission, along with energy demand reduction decarbonization of the energy supply sector is also required. The energy models used to analyze building-sector emission often assume various emission factors to project the emission in different time period. That is why it is difficult to compare the emission projections of the different energy models. However, still, to provide a general trend of the emission, this study discusses the global trend, more precisely the emission mitigation potential of the building sector globally provided by different energy demand models. For instance, both HEB and BUENAS model predicts 29% and 13% GHG emission reduction respectively by 2030 compared to their baseline scenario if mitigation measures are taken. As per Urge-Vorstaz et al. (2012) by the year 2050, 41% emission reduction is possible globally from the building sector compared to the baseline (2010 level) scenario.

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Different models provide a different range of results due to various scenario-related assumptions and different methodologies used in the model. Thus, the magnitude of the different end-use demand may change if scenario-related assumption changes, but the trend gather from different energy demand remains the same. More precisely, the trend suggests if no further policy/action is taken, then building energy demand rise immensely and ambitious climate policies/actions, it is possible to reduce the building sector energy demand. Another observation can be made from this review which is, most of the building-sector demand models are closed models and hence, it is difficult to compare their results, but a trend can be derived from these different results produced by different energy models. In most cases, the assumption of the models and their mathematical equations are also not open which makes them a 'black box' and hence arises difficulty in the time of comparing the results of different energy models. More such issues are discussed in section 3.1.1.1 below.

3.1.1 Critical issues with modelling energy demand for the building sector:

Energy models usually assume some underlying structural relationships with the economy to be constant or vary in a gradual fashion. For instance, people may not rely on government policies to mitigate emissions but rather they can start voluntary actions to mitigate global warmings. These structural assumptions may oversimplify the energy system. Further, the forecast of energy demand often makes presumption about human conduct and innovations that evolves gradually. Laitner et al. (2003) study identified some of the reasons which include an inaccurate description of the behavior of economic agents, inadequate inclusion of both environmental and social impacts, and lack of adequate technological details, due to which modelling projections often vary from the real data. In some cases, these changes in individual behavior or technological innovation occur in ways that we cannot anticipate. Thus, static energy models often misinterpret the real world because sometimes the changes are unpredictable and unforeseeable (Craig et al. 2002). Furthermore, data availability is another key issue with projecting demand precisely. Data are limited and often incomplete, and thus, few important characteristics of the energy system or economy may not be incorporated in the model. Along with these general issues with modelling energy demand, there are some building sector specific issues of energy demand models. Energy demand modelling for the building sector has three key issues related to; 1) modelling of lock-in effect, 2) integration of both energy efficiency measures and renewable energy sources, and 3) modelling of individual behavior. Each of these issues is discussed in the section below:

1) **Modelling of lock-in effect:** The lock-in more precisely carbon lock-in limits technological, economic, political, and social efforts to reduce carbon emissions (Seto et al. 2016). Carbon lock-in possesses several challenges towards limiting global warming at 1.5°. There are three major ways by which lock-in can limit the potential of a mitigation strategy: (a) technological and infrastructural lock-in: this type of lock-in is associated with the technologies and infrastructure which influence energy supply and hence, indirectly or directly emits CO2. For instance, investment in long-lasting built infrastructure such as buildings, land use patterns, influence the energy demand patterns as the components of the built environment determine energy demand for a considerable length of time after their development (Seto

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et al. 2016). This way, investment in long-lasting built infrastructure, which is not energy efficient by design, would result in carbon lock-in. (b) institutional and governance lock-in: Institutional and governance type of lock-in affect energy production and energy demand. Institutional and governance lock-in is a characteristic of institutions and type of governance that arises through the coevolution of multiple systems such as 'technological, economic, scientific, political, social, institutional, and environmental spheres' (Könnölä et al. 2006; Seto et al. 2016). For instance, the government often reduces the unit prices of electricity and formulate policies to expand coal-based electricity (Foxon 2002). As a consequence, the demand for electricity increases and hence, carbon emission from electricity consumption would also increase. (c) Behavior lock-in: Individual behavior and habits, are often influence energy consumption. Habits such as heating and cooling habits- use heater/cooler when it is required, use (or misuse) of appliances-for example switching off the appliances after use, have significant energy and emissions implications by locking-in the rate and magnitude of any mitigation measure (Shove and Walker 2014; Seto et al. 2016). The socio-technical structure of society often shapes consumers' choices towards more energy-consuming ways of life (Maréchal 2010). Thus, in other words, it is safe to conclude that institutional and governmental lock-in can result in a behavioral lock- in.

Along with these three kinds of lock-in, there is another type of lock-in which can be referred to as adaptation-time lock-in. Adaptation of new technologies often takes time and hence there is a risk of compromising with an inferior technology instead. Studies (see (Norberg-Bohm 1990; Mulder 2005; Urge-Vorstaz et al. 2012) show that in the short to a medium-term like 2030 to 2050, the adoption of new energy-saving technologies could significantly reduce energy use. As cited in Urge-Vorstaz et al. (2012) study that "the main reason for the lock-in effect is the delay in adoption and slow diffusion of new and more efficient technologies" (Urge-Vorstaz e al. 2012). These existing technologies, institutions, and behavioral norms together often compel the rate and the scale of carbon emissions reductions. Understanding the nature of lock-in would help in identifying the alternative paths and strategies to achieve full mitigation potential (Seto et al. 2016). However, till now, most of the building models do not incorporate lock-in rigorously and thus, as a result, the projection of future energy demand may not provide a comprehensive picture of the future energy demand. Moreover, the potential climate change policies may be seen as under-achiever due to these lock-in effects and hence would result in underinvestment. Among all the building models reviewed in this study, only High efficiency building (HEB) model calculates the lock-in effect as the difference between thermal energy use levels achieved under two scenarios: moderate efficiency scenario and deep Efficiency with respect to the base year. However, this HEB model does not differentiate between different types of lock-in.

2) **Integration of renewable and energy efficiency measure:** Renewable energy sources and energy efficiency measures to meet building energy demand are essential to curb down global temperature rise. Although many of the energy models do show the potential of different energy efficiency measures and renewable energy use to meet the energy demand from building sector under different scenarios, but there are almost no model which

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investigates the potentiality of the integrated system- meaning combination of both energy efficiency measures and renewable energy use to meet building sector energy demand. However, it is crucial to explore the feasibility of the use of renewable energy- more precisely, explore the possibility of whether a sufficient amount of renewable energy is available to meet the building energy demand. Furthermore, in the building sector, the importance of smart grid or smart buildings has gained interest recently, but until now, majority of the building sector-related energy models have projected energy demand by using a component-oriented approach which means energy models often consider building as a sum of separate components. This approach lacks the complexity of the building systems and hence, ends up delivering an over-simplified analysis of the energy demand (Urge-Vorstaz et al. 2012). Thus, the feasibility of the integrated approach of incorporating both renewable energy sources and energy efficiency measures to meet energy demand is required in order to project the building energy demand more accurately.

3) **Modelling of human factor:** Most of the building-related energy models do not incorporate human factors. The human factors such as occupant choices, lifestyle, and behavior in buildings, significantly affect energy consumption (Abergel et al. 2017). It is often the case that the design of a building influences the occupant's feeling of comfort and hence, influences the energy demand of the building. Modelling of human factor or modelling of behavioral lock-in should definitely be incorporated in the model that projects the energy demand of the building. For example- energy efficiency measures such as daylight harvesting, passive heating and cooling would certainly reduce the energy consumption of the occupant only if the occupant has adopted these measures successfully.

3.2 Transport sector:

Transport or mobility plays a key role in the human well-being, and economic development and studies show (Kahn Ribeiro et al. 2007; Moriarty, and Honnery, 2008) that globally transport activities are increasing as economies grow. The transport sector globally was responsible for approximately 23% of total energy-related CO2 emissions which is equivalent to 6.7 GtCO2 in 2010 (Sims et al. 2014). As per IPCC fourth assessment report, despite the increasing share of energy-efficient vehicles, the growth in the transport sector related GHG emissions has continued. More precisely, globally emissions from the transport sector have increased by 2% annually during the period of 2000-2017, which equivalents to 8 GtCO2 (IEA 2019). The key issues with transport sector activities are associated with petroleum dependence, air pollution, traffic fatalities and injuries, and congestion (Kahn Ribeiro et al. 2007). The intensity of oil dependence of transport is almost the same in developed and developing nations. For instance, in the EU, 94% of the energy needs from the transport sector are met by oil (European Commission 2016). Thus, in order to decarbonize the transport sector, the transport sector needs to get rid of its oil dependence. Here it is important to understand that the emission potential is the same from passenger and freight transport sector, while the road sector offers the biggest extent of mitigation potential (SLoCaT 2018). Presently the majority of the road transport vehicles and equipment are powered by internal combustion engines (ICEs), where gasoline and diesel are used as the main fuels for Light-duty vehicles (LDVs) and 2- and 3-wheelers (Sims et al. 2014). Diesel is used for Heavy-duty vehicles (HDVs) and diesel or heavy fuel

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oil, and grid electricity is used for the trains. From this trend, the petroleum dependence of the transport sector gets clearer. Therefore, the mitigation techniques should be designed primarily focusing on road transport sector.

Decarbonization of the transport sector requires either through demand control or through technological improvement. For instance, the total demand for motorized transport can be reduced by encouraging active transportations (such as walking, cycling, and use of public transport). An expansion of public transport and improvement in the infrastructure for active transportation in cities could obtain up to 40% reduction of urban passenger transport emissions by 2050 (Huizenga et al. 2017). Moreover, switching to high-efficiency vehicles which include electric vehicles, battery vehicles, is another option to reduce emissions from the transport sector (Pietzcker et al. 2014). There are other alternatives to mitigate the emission from the transport sector by using clean fuels such as advanced biofuels, hydrogen and renewable synthetic fuels. For example, as per the European Commission 2016 fact sheet, 15-17% of oil demand by the transport sector can be replaced by low-emission energy in 2030 (European Commission 2016). However, to keep the global warming at 1.5 degrees, the emission from transport sector cannot be more than 2-3 gigatonne (Gt) emissions/year by mid-century (Huizenga et al. 2017) which is equivalent to around 68% emission reduction compared to the present emission scenario. Therefore, to achieve the 1.5-degree target, both modal shift and technological improvement to energy-efficient vehicles are required.

It is often the case that the policymakers struggle to develop comprehensive policy packages to achieve a low-carbon transport system, as most of the policy options/strategies only consider technological advancement with an assumption of societal and personal preferences being unchanged. For instance, in the UK, national strategy development is mostly formed mostly by gathering data from techno-economic modelling of the energy system and/or the transport system (Brand et al. 2012). Thus in the table below of the key transport models are discussed:

Table 2: List of energy demand models for the transport sector

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Model name	**Host institution**	**Time span**	**Geographic coverage**	**Modelling method/approach**	**Description of the model (some key assumption, a brief description of the model, specific end-use analysed)**	**Key drivers**	**License (Open/close)**	**Key relevant papers/reports**
Assessment of Transport Strategies- ASTRA model	Fraunhofer-ISI, IWW Karlsruhe and TRT Trasporti e Territorio	2050	EU 27 member states	ASTRA is an integrated assessment model which uses simulation methodology to link transport module with macro-economic module.	The model is based on the System Dynamics approach to interpret nine modules which includes vehicle fleet model, transport model, emission and accident models. Moreover, ASTRA covers a wide scope of strategies with adaptable planning and levels of approach execution. Potential policies incorporate standard setting, fuel tax assessment, speed limits, carbon charges, and so on.	-Macro – economic parameters -Fuel use -Population	Open	http://www.astra-model.eu/ Fiorello et al. 2010
GCAM	Pacific Northwest National Laboratory	2100	Global	GCAM uses a logit choice formation method to model various mode of transport.	GCAM model uses logit choice formation technique to model passenger transport, freight transport, international shipping with the demand of the each transportation service along with the population. Moreover, this model considers the competition	-Micro and macro-economic parameters -Fuel type used -Cost of infrastructure	Open	Pietzcker et al. 2014

					between different modes of transport by using a logit choice mechanism. GCAM model analyse the social cost of using different modes of transport globally.	-Modes of transport		
PRIMES-TREMOVE	E3M Lab, NTUA	2000-2050	EU-27 member states	This model uses a simulation technique to model transport-related activities.	The PRIMES-TREMOVE is a dynamic system of multi-agent choices of different transport activities. The projection is done by considering several factors which includes choices related to economic, and technology of transportation. Moreover, this model incorporates costs (operation costs, investment costs, emission costs, taxes), congestion, and other public policies, which influence the choice of transportation modes. The PRIMES-TREMOVE model comprises of two principle modules, the transport demand allocation module and the technology choice and equipment operation module. The two	-Economic parameters -Stock of different modes -Type of fuel used in different modes	Unknown	Capros,, & Siskos, 2012

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					modules communicate with one another and are comprehended at the same time.			
World Induced Technical Change Hybrid- Transport (WITCH-T) model	Fondazione Eni Enrico Mattei	2100	Global	WITCH-T models uses both bottom-up and top-down approaches, in other words hybrid approach to project mobility demand for all the transportation modes.	In this model, the mobility demand is exogenously anticipated dependent on the local GDP and vehicle proprietorship. In order to calculate the final energy demand from the mobility demand, WITCH-T model uses investment- more precisely investment in different vehicle technologies.	-Economic parameters -Investment -Cost -Energy usage	Unknow n	Pietzcker et al. 2014
REMIND	Potsdam Institute for Climate Impact Research	2100	Global	REMIND uses a hybrid approach to project the energy demand from the transport. Moreover, it uses a inter-temporal optimization technique to model energy demand for the 4 transport sub-sectors.	REMIND model determine the energy demand from the transport sector by using a hybrid approach. More precisely, mobility demands for the four sub-sectors namely passenger-light duty vehicles (LDV), freight, electric rail, passenger-aviation and buses) are derived by using a top-down approach, and for the LDV mode, different technology options are	-Economic parameters -Investment costs -Technological details for different mode of transports	Unknow n	Pietzcker et al. 2014

					available, hence, a linear bottom-up approach is used to incorporate these technological details.	-Efficiency improvements		
Transport Integrated model of Europe (TRIMODE)	TRT Trasporti e Territorio, PTV AG, E3MLab, MDS Transmodal ,Bauhaus Luftfahrt, M-Five, Fraunhofer-ISI, INRIX	2015-2050	Europe	TRIMODE model uses stimulation technique to project energy demand of the transport sector in Europe. Furthermore, it uses a two-layer General Equilibrium method to determine the macroeconomic parameters.	This model considers four modules: passenger and freight movements across Europe, energy module, and economy module. This model is used to understand the comprehensive range of infrastructure investment, pricing, technology and regulatory policy scenarios-related to transport sector in Europe. TRIMODE uses the PTV Visum platform, GAMS software and Python scripts to estimate the future energy demand for these four transport modules.	-Macroeconomic parameter -Vehicle stock -Energy prices -Technological details	Unknown	Fiorello et al. 2018 http://www.trt.it/en/ PROGETTI/trimode_project/
Multi-Agent transport Simulation (MATSim)	ETHZ	2030	Global	MATSim uses a large-scale agent-based simulation method to project the energy demand from the transport sector, and the traffic flow of a	MATSim model is an activity-based, extendable, multi-agent simulation model. It is an open-source model-meaning it can be downloaded easily from the web. This model provides a framework for demand-modeling, agent-based	-Economic parameters -Vehicle stock -Travel demand	Open	Horni et al. 2016 https://www.matsim.org/ about-matsim

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				country/region. This model is implemented in Java.	mobility, precisely traffic-simulation, and a controler to iteratively run simulations along with the methods to analyze the output which are generated by the different modules.			
UK Transport Carbon Model (UKCM)	UKERC	2050	UK	UKTCM is a highly disaggregated model which uses bottom-up approach to model the energy service demand of the transport sector in the UK.	This model incorporates different vehicle choices by incorporating different modal choice and trip patterns which influence the transport service demand. To elaborate this further, UKTCM model provides annual projections of supply and demand by the transport sector, for all passenger and freight transport, and also it calculates the corresponding annual energy use, life cycle emissions and environmental impacts.	-Economic parameters -Demographics -Car ownership	Unknown	Brand et al. 2012 Anable et al. 2012
Transport European Simulation Tool-(TRUST)	TRT	2016-2050	Europe	TRUST model uses a simulation technique and is built in PTV VISUM software.	TRUST is a transport network model which analyses the assignment of Origin-Destination matrices for passenger and freight	- Speed-flow functions - Transport costs by mode	Unknown	TRT (2018) http://www.trt.it/wp/wp-content/uploads/20

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					transport demand. The main output of this model is the load on road network links and it is presented as vehicles per day. Moreover, TRUST model also present data on non-road links in terms of number of trips and/or tonnes per day.	- Values of travel time - Average fuel consumption - Emission factor		16/09/TRUST-model-detailed-description-1.pdf
Battery electric vehicles potential (BEVPO) model	ETHZ		Selected EU countries	BEVPO model uses a stimulation technique to evaluate trips as shares of charging and non-charging events. BEVPO is developed by using an object-oriented Java program.	BEVPO model does not only evaluate the potentials of BEV but, moreover it looks at driving patterns of the electric vehicles and based on that evaluates the vehicle stock, charging and infrastructure policies. BEVPO can be used to understand the traffic load pattern of a nation.	-Vehicle stock -Car trips -Geo-spatial data for charging station coordinates	Unknown	Melliger et al. (2018)

Source: Own elaboration

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The mode of transport for a personal trip is determined by various factors which include distance to the nearest center, travel cost, land-use, travel time, personal preference (Scheiner 2010; Zhang et al. 2017). The choice for mode of transport further determines the travel demand and transport-related emissions. Thus, transport-related energy demand models estimate the travel demand by incorporating the modal split.

Table 2 shows several such models that are used to project/estimate the energy needs of the transport sector. From these reviewed models, it is considered that transport-related emission mitigation policies would include the following:

- Speed control,
- Fuel efficiency
- Traffic signal coordination,
- Vehicle efficiency
- Battery/electric vehicles
- Intelligent Transport System (ITS),
- Public transport improvement,
- Land use planning
- The modal shift towards public transport and active transportation
- Carbon capture storage (CCS)

Most of the mitigation techniques aimed at the transport sector can be structured by the Avoid-Shift-Improve (A-S-I) framework (SLoCaT 2018). Each of the components of A-S-I framework is discussed below:

- **Avoid:** This component of A-S-I framework emphasizes avoid mechanism where a rider/passenger avoids any travel done by motorized mode. Public transportation improvement is an excellent example of avoid component where improvement in public transportation would reduce travel distance by individual motorized modes of transport.
- **Shift:** If passengers and freight travel shift towards a sustainable mode of transport such as walking or cycling then this 'shift' can achieve a significant emission reduction target.
- **Improve:** Unlike avoid and shift component, improve is more of a supply-side mechanism which focuses on improving the energy efficiency of transport modes and vehicle technologies. Speed control and traffic signal coordination are two good examples of improve approach.

Despite this precise decarbonize framework and different mitigation options to decarbonize the transport sector, it is still a big challenge to decarbonize the transport sector. One of the key reasons behind this challenge is the fact that the mobility sector in general respond less to the mitigation options/policies compared to the other sectors (Schäfer and Jacoby 2006; Banister et al. 2011; Pietzcker et al. 2014). Moreover, as it is discussed at the beginning of section 3.1.2, the transport sector is dependent on fossil fuel and its demand remains persistent (Pietzcker et al. 2014). However, different energy demand models reviewed in table 2 show a substantial potential to achieve significant emission reduction by mid-century. For instance, three models namely REMIND, WITCH-T and GCAM used in Pietzcker et al. (2014) study show us that the transport sector globally

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can achieve up to 90% emission reduction by end of the century compared to the baseline scenario. Both the GCAM and REMIND model develop their mitigation scenario by incorporating fuel efficiency, with the use of CCS. Precisely, these models develop their mitigation scenario with the reliance of liquid fuels- more precisely 85% of the transport-related final energy is met from liquid fuel even in the stringent mitigation policy scenarios (Pietzcker et al. 2014). Thus, these models show that despite heavy liquid fuel reliance of transport sector, it can still achieve a substantial mitigation potential by improving fuel efficiency and demand management. In addition to the fuel efficiency, if the transport sector switched to the cost-effective battery electric cars until 2050 then emission from transport sector can be further reduced (this includes the fact that indirect emissions from electricity generation are still occurring) (Creutzig et al. 2015). Melliger et al. (2018) study uses the BEVPO model to show that battery electric vehicles (BEVs) 85–90% of all national trips in Switzerland and Finland "could have been covered with BEVs prevalent in 2016". Furthermore, this study also argues that with BEVs it is possible to provide a road network coverage as high as 99% in both Switzerland and Finland provided, proper charging station infrastructure is in place and high-range BEVs are adopted. Moreover, energy models such as ASTRA and TRUST show that emission reduction through mobility management would also result in other co-benefits such as improvement in GDP, employment generation (Schade et al. 2018).

3.2.1 Critical issues with modelling energy demand for the transport sector:

Similar to the building sector, modelling of the energy demand of the transport sector does have some major issues-related to modelling lock-in effects or incorporating individual behavioral effects. More precisely, similar to the building sector, institution lock-in (for example unsustainable land–use) may result in behavioral lock-in (for example, using cars to commute even for the short distance). The lock-in effects would eventually undermine the potential of any sustainable transport policy. Moreover, as discussed in the above section, the choice of mode is based on several factors which include individual preference as well. Thus, incorporating individual preferences into demand model would enhance the projection accuracy of the models. As it can be seen from table 2 that there are many transport models that incorporate individual modal splits and in order to incorporate individual modal split, these models use a discrete choice approach (Zhang et al. 2017). With a discrete choice approach although individual preference can be incorporated, but these discrete choice models/logistic models are unable to project the aggregate impacts such as overall emission from transport, or total demand for fuel. Hence, transport models that incorporate individual preferences although provide a clear picture about the future modal split or potential of a particular efficiency measure such as battery cars but, these models do not give a broader picture of its environmental impacts. Thus, usually unable to project the aggregate impacts.

4.Discussion:

As discussed in section 1.2, the demand for both primary and final energy has been continuously increasing over a decade as a result of population growth, and economic (unsustainable) development. This consistent rise in energy demand also results in higher energy related GHG

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emission as globally the energy system is still petroleum dependent. The share of renewable energy sources is still outweighed by the share of non-renewable energy sources such as coal, oil, and natural gas in order to meet the energy demand globally. Moreover, the level of investment in energy efficiency remains almost unchanged since 2014 (IEA 2020,7th February). As per IPCC (2018) report, "global warming is likely to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate". These key trends indicate towards a policy gap and also it suggests immediate actions to reduce energy related GHG emission. More precisely, to limit global warming at 1.5 degrees, the energy system needs to be decarbonized, because if the energy system is decarbonized, then a higher demand for energy would result in no/negligible impact on global warming. However, the transition towards decarbonization is not easy and it is always subject to resource and time constraints. Further, lack of understanding of consumer activity/behavior, social norms and misinterpreting demand trends can lead to misallocation of resources. Thus, strategic evidence-based planning is required to frame policies to decarbonize the energy system, and hence, energy models play an important role to formulate the strategies (Li et al. 2019). However, as it is discussed in section 3.1.1.1 and 3.1.2.1, the energy demand models do suffer from some serious issues (such as lack of transparency, unable to incorporate behavior changes) which may project the future in a simplistic manner. Some of the common issues of energy modelling are discussed in the section below:

Data scarcity and energy demand modelling:

Throughout section 3.1.1 and section 3.1.2, we have discussed various energy demand models from the building and transport sectors. These models can help in generating evidence by projecting future energy demand and the associated cost. However, the results of these energy models may not be accurate as the models have some strict assumptions or drawbacks. More precisely, as Li et al. (2019) study argues that the energy models including the demand models are structured and created to work under conditions of information shortage. Thus, any projection done by these models is characterized by uncertainties. Moreover, in the absence of adequate information to develop future scenarios and statistical methods, the underlying baseline data is used to develop the methods for projection which may contain critical gaps, because these gaps would enforce a reductionist representation of the real world (Li et al. 2019). For instance, the building sector is heterogeneous in nature- meaning energy demand varies based on the type of buildings which includes residential and commercial building sectors. Even within commercial building sectors, there are different types of buildings such as office space, retail, warehouse which have different demand patterns. Thus, in order to model energy demand, different types of building need to be accounted as well. However, there is little-to-no data on energy demand for these different types of buildings across regions, and time. Therefore, baseline data with some strict assumptions is often used to model the energy demand pattern of these buildings. Similarly, for the transport sector, getting data of different modal splits, and demographic data for the modal splits at the national level are difficult to obtain which are the key input data required to model transport demand.

Data scarcity is probably the biggest challenge in modelling energy demand. Although there has been a significant advancement in data analyses through big data analysis, machine learning and artificial intelligence, but there are still major drawbacks in the existing energy models which need

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to be addressed with the help of big data incorporation. Modelling energy demand requires different types of data which include spatial, temporal, demographic data. Different energy demand models use different type of data as per the objective of the model and different types of data poses different types of challenges. Table 3 below describes some of the challenges associated with different types of data associated with energy demand modelling.

Table 3: Data scarcity and its associated challenges in the context of energy demand models

Data Types	**Challenges**
Spatial	Energy demand models require detail spatial disaggregation to project and analysis energy demand for any activity. For instance, in order to model heating/cooling intensity and appliance ownership, models require spatial disaggregation data- more precisely data at regions, rural/urban level. This spatial disaggregation often is based on some strict assumptions due to data scarcity.
Temporal	The demand for energy varies during different periods such as day, night, or different seasons. For instance, during office hour the number of vehicles is the highest compared to other time periods. Thus, data on both number of vehicles in the road along with the modal split in different time period are required to model energy demand of transport sector realistically. Data scarcity to incorporate temporal aspect could lead to inaccurate projection of future scenarios.
Technological	Many of the energy demand models especially the building sector models often use bottom-up approach which requires technological data in detail. In the absence of detail technological data, often simplistic aggregation is done which can lead to simplification of the demand, and inadequately differentiate between new technology investments.
Socio-economic and demographic	Similar to technological data, socio-economic and demographic data are required when bottom-up approach is used. Furthermore, without socio-economic and demographic data the distributional impacts of different policies.
Behavioral data	Majority of the energy demand models assume consumer/user behavior to be constant over time. However, studies have revealed that behavioral changes can significantly impact energy demand (Masoso, &

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Data Types	Challenges
	Grobler 2010; Sorrell 2015). Thus, incorporation of behavioral data would make the demand models more realistic.
Stock data	For most of the energy models (as it can be seen from the energy models reviewed in section 3.1.1 and 3.1.2) require detail stock data to model energy demand realistically. Few of the key stock data (for example, building stock, vehicle stock, stock of different types of retrofitted buildings, and many more) are necessary to project future energy demand. Therefore, unavailability of stock data may lead towards inaccurate/unrealistic demand projection.

Source: Own elaboration (adopted from Li et al. (2019) study in the context of energy demand modelling)

With the advancement of methodologies of different energy models, new data gaps are identified almost every day. These data gaps are forcing energy models to make some strict assumptions that lead towards a simplistic analysis of energy demand. The challenges identified in table 3, need special attention while developing or running a model. Especially now with the objective of transition towards zero-carbon society, energy models require a huge chunk of disaggregated data through which projection of demand and planning of resources can be made more precisely.

Energy demand and limiting global warming at 1.5 degree:

The Paris agreement to limit global warming to 1.5 °C by 2100 generates challenges to find the optimum ways to succeed in achieving this goal and hence, it also generates an opportunity to understand the possible mitigation ways to achieve this goal (Hulme, 2016; Pedde et al., 2019). As it is discussed in section 3.1.1, to keep the global warming by 1.5-degree target, 60 Gt of CO2 emissions reduction is required between 2010 and 2050 from the building sector globally (Wang et al. 2018). Similarly, transport-related emissions should be reduced to 2 to 3 Gt of CO2 globally by 2050 which is equivalent to about 70 to 80% emission reduction below 2015 levels to meet the targets set in the Paris Agreement (SLoCaT 2018). Moreover, due to lock-in effects-for example, building and transport infrastructure-related decisions would lock-in both energy demand for building and transport for decades to come, and achieving Paris Agreement targets by 2050 will be difficult if the transition towards low carbon society is not started at the earliest time possible (Ürge-Vorsatz et al. 2018; SLoCaT 2018). Thus, both the supply side as well as the demand side mitigation, are required to achieve such an ambitious target for these two sectors. However, so far only the supply side mitigation techniques and carbon dioxide removal (CDR) options along with storage technologies, particularly bioenergy with carbon capture and storage (BECCS) are emphasized as mitigation strategies (Mundaca et al. 2019). In other words, the demand-side solutions tend to be neglected in the 1.5-degree scenarios. Thus, a comprehensive understanding of demand side solutions would not only minimize the risks (for example, excessive reliance on large scale CDR options, or reliance on management of different solar radiation technologies) associated with supply side strategies, but also demand-side options have an immense potential to obtain multiple

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impacts/co-benefits such as improvement in health, less pollution, energy security, equity, higher well-being, and many more (Ürge-Vorsatz et al. 2016; Creutzig et al. 2016; Chatterjee et al. 2018; Mundaca et al. 2019). Therefore, the demand side options should be incorporated into the energy models. With more rigorous and systematic modelling efforts, the role of the demand side mitigation strategies would provide more risk-free options to achieve the 1.5-degree goal.

Assumptions of the energy demand models:
As it is discussed in the above paragraph that in the absence of detail, the energy demand models often make some simplistic assumptions to build a model. Some of the assumptions although may have made due to the absence of data, but there are some assumptions that are structural, or scenario related. These assumptions may represent the economy/energy system in an over-simplistic way. In general, the assumptions made in different energy models can be divided into three categories:

1. Structural assumption: This kind of assumption is made about the certain structure of the society or economy or about energy systems. One such structural assumption which is often considered in energy demand models, is assuming symmetric price elasticity between energy price and energy demand. More precisely, symmetric price elasticity refers to the symmetric response to price increase/decrease in energy demand. However, studies have argued that it is not necessarily the case. As per these studies "energy demand response to the price increase is not necessarily reversed completely by an equivalent price decrease, nor is the demand response to an increase in the maximum historical price necessarily the same as the response to a price recovery" (Salisu and Ayinde 2016). This assumption of symmetric price response can misread other economic indicators (for example as well GDP of a nation, employment, energy security).
2. Scenario-related assumptions: Majority of the energy demand models present their data for different scenarios which help the policymaker to decide on the type of policies. However, to project data for different scenarios, often some stringent assumptions are made. For instance, the HEB model made an assumption about technology mixes for different regions for different scenarios. In addition, an average achievable efficiency was assumed for each individual technology for each region to determine the water heating efficiency (Urge-Vorstaz et al. 2012). The scenario-related assumptions have become necessary as it often the case that input data for future scenario projection are not available.
3. Methodological assumption: Different models make diverse assumptions based on the modelling objective and methodology used in the model. In other words, methodological assumptions can vary as per different models. These methodological assumptions sometimes oversimplify the scenario. For instance, models using a bottom-up approach often make assumptions about macro parameters. However, these methodological assumptions are mostly made due to the absence of data. Thus, data scarcity and methodological assumptions are interrelated.

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In any empirical model, there are always some assumptions made as it is not possible to get all the present, past, and future data for the parameters. For instance, in most of the cases, the scenario-related assumptions are necessary to build the scenarios as parameter data under different scenario is not available. Thus, having assumptions should not be seen as a weakness. However, some of the assumptions, mostly structural and methodological assumptions may oversimplify the models, but due to data scarcity, there are no other options left than making an assumption. Hence, the nature of the assumptions should be examined thoroughly for any model.

Next steps:
This study provides an understanding of the current demand trends and on some of the key energy demand models of the building and transport sector. From the existing trends, it is clear that the role of energy models would be crucial to design and implement policies to limit global warming by 1.5 degrees. Moreover, the energy demand models need to as transparent as possible. Thus, both models' methodological framework and their assumptions with coding should be openly available. There are some major challenges regarding the data availability which are discussed in this study. These data challenges need to be identified before running a model and accordingly, models need to be designed/ modified. In case of other methodological challenges such as incorporating lock-in effects, integrating renewable energy sources, should get incorporated into the model as much as possible. Moreover, quantification of the variability of energy demand as per time and location is necessary to understand the practicability of energy transition. Accordingly, quantification of the shape and variability of weather dependent renewable energy sources would be conducted to understand the feasibility of the renewable energy sources to meet energy demand. This report provides a list of issues that needs to be tackled by identifying and discussing the issues-related to energy models. As the next step, the SENTINEL project would do the following:

- Try to upgrade/modify the demand models such as DESTINEE, HEB, BEVPO, and DREEM as much as possible. This upgradation/modification would further help the models to represent the demand component more precisely.
- The output of the models will be linked to the user-needs identified in deliverable 1.2. This linking would be a gap analysis as well which would further improve the models.
- Including economic and transition data as input to the demand models in collaboration with WP 2 and WP 5. This incorporation of data would emphasis the role of demand in the energy transition.
- Lastly, this input from demand then can further be incorporated into the system model in order to provide a precise picture of the energy system transition. Moreover, different case studies will be conducted using this model. This will entail calibrating the model data to the details of the case study region.

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References

Abergel, T., Dean, B., & Dulac, J. (2017). Towards a zero-emission, efficient, and resilient buildings and construction sector: Global Status Report 2017. UN Environment and International Energy Agency: Paris, France.

Abergel, T., Dean, B., & Dulac, J. (2017). Towards a zero-emission, efficient, and resilient buildings and construction sector: Global Status Report 2017. UN Environment and International Energy Agency: Paris, France.

Anable, J., Brand, C., Tran, M., & Eyre, N. (2012). Modelling transport energy demand: A socio-technical approach. Energy policy, 41, 125-138.

Banister, D., Anderton, K., Bonilla, D., Givoni, M., & Schwanen, T. (2011). Transportation and the environment. Annual Review of Environment and Resources, 36, 247-270.

Boßmann, T., & Staffell, I. (2015). The shape of future electricity demand: exploring load curves in 2050s Germany and Britain. Energy, 90, 1317-1333.

Bhattacharyya, S. C. (2011). Energy economics: concepts, issues, markets and governance. Springer Science & Business Media.

Bhattacharyya, S. C., & Timilsina, G. R. (2009). Energy demand models for policy formulation: a comparative study of energy demand models. The World Bank.

Boermans, T., Bettgenhäuser, K., Offermann, M., & Schimschar, S. (2012). Renovation Tracks for Europe up to 2050: Building renovation in Europe what are the choices. Ecofys Germany GmbH.

Böhringer, C., & Rutherford, T. F. (2008). Combining bottom-up and top-down. Energy Economics, 30(2), 574-596.

BP British Petroleum. (2016), Statistical Review of World Energy. United Kingdom: BP British Petroleum.

Brand, Christian, Martino Tran, and Jillian Anable. "The UK transport carbon model: An integrated life cycle approach to explore low carbon futures." Energy Policy 41 (2012): 107-124.

Capros, P., & Siskos, P. (2012). PRIMES-TREMOVE Transport Model v3 Model Description.

Chatterjee,S., Ürge-Vorsatz,D., Thema,J., Kelemen,A.. (2018). Synthesis Methodology D2.4 Final report-COMBI project.

Craig, P. P., Gadgil, A., & Koomey, J. G. (2002). What can history teach us? A retrospective examination of long-term energy forecasts for the United States. Annual Review of Energy and the Environment, 27(1), 83-118.

CREDS (2019). What is Energy Demand? Accessed in 10th October 2019. https://www.creds.ac.uk/what-is-energy-demand/

Creutzig, F., Fernandez, B., Haberl, H., Khosla, R., Mulugetta, Y., & Seto, K. (2016). Beyond technology: demand-side solutions for climate change mitigation. Annual Review of Environment and Resources, 41, 173–198.

Creutzig, F., Jochem, P., Edelenbosch, O. Y., Mattauch, L., van Vuuren, D. P., McCollum, D., & Minx, J. (2015). Transport: A roadblock to climate change mitigation?. Science, 350(6263), 911-912.

Daioglou, V., Van Ruijven, B. J., & Van Vuuren, D. P. (2012). Model projections for household energy use in developing countries. Energy, 37(1), 601-615.

Economidou, M., Zangheri, P., Müller, A., & Kranzl, L. (2018). Financing the Renovation of the Cypriot Building Stock: An Assessment of the Energy Saving Potential of Different Policy Scenarios Based on the Invert/EE-Lab Model. Energies, 11(11), 3071.

Energy and Environmental Policy Center, John F. Kennedy School or Government.

European Commission - Fact Sheet (2016). A European Strategy for low-emission mobility. https://ec.europa.eu/commission/presscorner/detail/en/MEMO_16_2497

European Commission (2018)-Statement. Europe leads the global clean energy transition: Commission welcomes ambitious agreement on further renewable energy development in the EU.

Filippini, M., & Hunt, L. C. (2011). Energy demand and energy efficiency in the OECD countries: a stochastic demand frontier approach. The Energy Journal, 59-80.

Fiorello, D., Fermi, F., & Bielanska, D. (2010). The ASTRA model for strategic assessment of transport policies. System Dynamics Review, 26(3), 283-290.

Fiorello, D., Nökel, K., & Martino, A. (2018). The TRIMODE integrated model for Europe. Transportation Research Procedia, 31, 88-98.

Fleischman Napadenschi, J. (2015). Exploring the energy demand of the service sector and its role in global emissions. Utrecht University, Faculty of Geosciences Theses (Master thesis). https://dspace.library.uu.nl/handle/1874/334201

Fleiter, T. et al. (2016) Mapping and analyses of the current and future (2020 - 2030) heating/cooling fuel deployment. Project for the European Commission.

Foxon, T. J. (2002). Technological and institutional 'lock-in'as a barrier to sustainable innovation. Imperial College Centre for Policy and Technology Working Paper.

Fritz, S., 2016. Economic assessment of the long-term development of buildings' heat demand and grid-bound supply. A case study for Vienna. PhD-Thesis at Technische Universität Wien, Fakultät für Elektrotechnik und Informationstechnik, Wien.

Grubb, M., Edmonds, J., Ten Brink, P., & Morrison, M. (1993). The costs of limiting fossil-fuel CO2 emissions: a survey and analysis. Annual Review of Energy and the environment, 18(1), 397-478.

Güneralp, B., Zhou, Y., Ürge-Vorsatz, D., Gupta, M., Yu, S., Patel, P. L., ... & Seto, K. C. (2017). Global scenarios of urban density and its impacts on building energy use through 2050. Proceedings of the National Academy of Sciences, 114(34), 8945-8950.

Horni, A., Nagel, K., & Axhausen, K. W. (Eds.). (2016). The multi-agent transport simulation MATSim. London: Ubiquity Press.

https://ec.europa.eu/transport/sites/transport/files/studies/ten-t-growths-and-jobs-methodology.pdfhttps://europa.eu/rapid/press-release_STATEMENT-18-4155_en.htm

Huizenga, C., General, S., & Peet, K. (2017). Transport and Climate Change: How Nationally Determined Contributions can Accelerate Transport Decarbonization. Retrieved from. NDC Partnership http://ndcpartnership. org/sites/default/files/NDCP_Expert_Perspectives_ SLoCaT_Transport_v4. pdf (Last accessed: November 6th 2018).

Hulme, M. (2016). 1.5 C and climate research after the Paris Agreement. Nature Climate Change, 6(3), 222.

IEA (2019). CO_2 Emissions from Fuel Combustion 2019. International Energy Agency. https://webstore.iea.org/download/direct/2505?fileName=CO2_Emissions_from_Fuel_Combustion_2019_Overview.pdf

IEA (2019). Market Report Series: Energy Efficiency 2019. International Energy Agency. https://webstore.iea.org/market-report-series-energy-efficiency-2019

IEA 2018. Global Energy and CO2 Status Report 2018. The latest trends in energy and emissions in 2018. International Energy Agency. https://webstore.iea.org/download/direct/2461?fileName=Global_Energy_and_CO2_Status_Report_2018.pdf

IEA 2020. Energy Efficiency 2019- The authoritative tracker of global energy efficiency trends. Accessed in 7th February 2020. https://www.iea.org/reports/energy-efficiency-2019

IPCC AR4 – published as the Fourth Assessment Report of the Intergovernmental Panel on Climate Change in 2007 (IPCC 2007)

IPCC, 2018: Summary for Policymakers. In: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. In Press.

Isaac, M., & Van Vuuren, D. P. (2009). Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. Energy policy, 37(2), 507-521.

Kahn Ribeiro, S., S. Kobayashi, M. Beuthe, J. Gasca, D. Greene, D. S. Lee, Y. Muromachi, P. J. Newton, S. Plotkin, D. Sperling, R. Wit, P. J. Zhou, 2007: Transport and its infrastructure. In Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report

SENTINEL

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 837089.

of the Intergovernmental Panel on Climate Change [B. Metz, O.R. Davidson, P.R. Bosch, R. Dave, L.A. Meyer (eds)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Knobloch, F., Mercure, J. F., Pollitt, H., Chewpreecha, U., & Lewney, R. (2017). A technical analysis of FTT: Heat—a simulation model for technological change in the residential heating sector. European Commission, Directorate-General for Energy.

Knobloch, F., Pollitt, H., Chewpreecha, U., Daioglou, V., & Mercure, J. F. (2019). Simulating the deep decarbonisation of residential heating for limiting global warming to 1.5 C. Energy Efficiency, 12(2), 521-550

Könnölä, T., Unruh, G. C., & Carrillo-Hermosilla, J. (2006). Prospective voluntary agreements for escaping techno-institutional lock-in. Ecological Economics, 57(2), 239-252.

Laitner, J.A., S. J. DeCanio, J. G. Coomey and A. H. Sanstand, 2003, Room for improvement: increasing the value of energy modeling for policy analysis, Utilities Policy, 11, pp. 87-94.

Lechtenböhmer, S., Grimm, V., Mitze, D., Thomas, S., & Wissner, M. (2005). Target 2020: policies and measures to reduce greenhouse gas emissions in the EU; final report.

Levine, M., Ürge-Vorsatz, D., Blok, K., Geng, L., Harvey, D., Lang, S., ... & Rilling, J. (2007). Residential and commercial buildings. Climate change, 20, 17.

Levesque, A., Pietzcker, R. C., Baumstark, L., De Stercke, S., Grübler, A., & Luderer, G. (2018). How much energy will buildings consume in 2100? A global perspective within a scenario framework. Energy, 148, 514-527.

Li, F. G., Bataille, C., Pye, S., & O'Sullivan, A. (2019). Prospects for energy economy modelling with big data: Hype, eliminating blind spots, or revolutionising the state of the art?. Applied Energy, 239, 991-1002.

Lucon, O. et al., 2014: Buildings. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel, and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 671–738.

Madlener, R., & Sunak, Y. (2011). Impacts of urbanization on urban structures and energy demand: What can we learn for urban energy planning and urbanization management?. Sustainable Cities and Society, 1(1), 45-53.

Maréchal, K. (2010). Not irrational but habitual: The importance of "behavioural lock-in" in energy consumption. Ecological Economics, 69(5), 1104-1114.

Masoso, O. T., & Grobler, L. J. (2010). The dark side of occupants' behaviour on building energy use. Energy and buildings, 42(2), 173-177.

This project has received funding from the *European Union's Horizon 2020 research and innovation programme* under grant agreement No *837089*.

McNeil, M. A., Letschert, V. E., & Ke, J. (2013). Bottom–Up Energy Analysis System (BUENAS)—an international appliance efficiency policy tool. Energy Efficiency, 6(2), 191-217.

McNeil, M. A., Letschert, V. E., & Ke, J. (2013). Bottom–Up Energy Analysis System (BUENAS)—an international appliance efficiency policy tool. Energy Efficiency, 6(2), 191-217.

Melliger, M. A., Van Vliet, O. P., & Liimatainen, H. (2018). Anxiety vs reality–Sufficiency of battery electric vehicle range in Switzerland and Finland. Transportation Research Part D: Transport and Environment, 65, 101-115.

Moriarty, P., & Honnery, D. (2008). Low-mobility: The future of transport. Futures, 40(10), 865-872.

Mulder, P., 2005.The economics of technology diffusion and energy efficiency

Müller, A., 2015. Energy Demand Assessment for Space Conditioning and Domestic Hot Water: A Case Study for the Austrian Building Stock (PhD-Thesis). Technische Universität Wien.

Mundaca, Luis, Diana Ürge-Vorsatz, and Charlie Wilson (2019). Demand-side approaches for limiting global warming to 1.5 C. 343-362.

Neshat, N., Amin-Naseri, M. R., & Danesh, F. (2014). Energy models: Methods and characteristics. Journal of Energy in Southern Africa, 25(4), 101-111.

Niamir, L., Filatova, T., Voinov, A., & Bressers, H. (2018). Transition to low-carbon economy: Assessing cumulative impacts of individual behavioral changes. Energy policy, 118, 325-345.

Norberg-Bohm, V., 1990. Potential for carbon dioxide emissions reductions in buildings, Energy and Environmental Policy Center, John F. Kennedy School or Government. Harvard University, Cambridge, MA.

Openmod (2019). Openmod- open energy modelling initiative. Accessed on 5th December, 2019. https://www.openmod-initiative.org/manifesto.html

Paez, A. F., Maldonado Muñoz, Y., & Ospino Castro, A. J. (2017). Future scenarios and trends of energy demand in Colombia using long-range energy alternative planning.

Patterson, M. G. (1996). What is energy efficiency?: Concepts, indicators and methodological issues. Energy policy, 24(5), 377-390.

Pedde, S., Kok, K., Hölscher, K., Frantzeskaki, N., Holman, I., Dunford, R., ... & Jäger, J. (2019). Advancing the use of scenarios to understand society's capacity to achieve the 1.5 degree target. Global Environmental Change, 56, 75-85.

Petrichenko, K. (2015). Duet of solar energy and energy efficiency and its role for net zero energy buildings. In ECEEE Summer Study Proceedings 2015: First Fuel Now.

Pietzcker, R. C., Longden, T., Chen, W., Fu, S., Kriegler, E., Kyle, P., & Luderer, G. (2014). Long-term transport energy demand and climate policy: Alternative visions on transport decarbonization in energy-economy models. Energy, 64, 95-108.

This project has received funding from the *European Union's Horizon 2020 research and innovation programme* under grant agreement No *837089*.

Pokharel, S., Ahmade, A. A., Al-Ansari, F. A., Al Allaf, H., Daneshvar, M. S., & AbdelQadir, A. M. (2012, January). Energy modeling for policy analysis. In Proceedings of the 3rd Gas Processing Symposium. A. Aroussi and F. Benyahia. Oxford, Elsevier (Vol. 3, pp. 199-208).

Psiloglou, B. E., Giannakopoulos, C., Majithia, S., & Petrakis, M. (2009). Factors affecting electricity demand in Athens, Greece and London, UK: A comparative assessment. Energy, 34(11), 1855-1863.

references, Cheltenham, UK: Edward Edgar Publishing Inc.

Ringkjøb, H. K., Haugan, P. M., & Solbrekke, I. M. (2018). A review of modelling tools for energy and electricity systems with large shares of variable renewables. Renewable and Sustainable Energy Reviews, 96, 440-459.

Rivers N, Jaccard M. Combining top-down and bottom-up approaches to energy–economy modeling using discrete choice methods. The Energy Journal 2005;26(11):83–106.

Roberts, S. (2008). Demographics, energy and our homes. Energy Policy, 36(12), 4630-4632.

Rogelj, J., D. Shindell, K. Jiang, S. Fifita, P. Forster, V. Ginzburg, C. Handa, H. Kheshgi, S. Kobayashi, E. Kriegler, L. Mundaca, R. Séférian, and M.V.Vilariño, 2018: Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development. In: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. In Press.

Salisu, A. A., & Ayinde, T. O. (2016). Modeling energy demand: Some emerging issues. Renewable and Sustainable Energy Reviews, 54, 1470-1480.

Schade, W., Hartwig, J., Schäfer,S..... Bellodi, L.(2018).The impact of TEN-T completion on growth, jobs and the environment METHODOLOGY AND RESULTS Final Report.

Schaefer, A., & Jacoby, H. D. (2006). Vehicle technology under CO2 constraint: a general equilibrium analysis. Energy Policy, 34(9), 975-985.

Scheiner, J. (2010). Interrelations between travel mode choice and trip distance: trends in Germany 1976–2002. Journal of Transport Geography, 18(1), 75-84.

Seto, K. C., Davis, S. J., Mitchell, R. B., Stokes, E. C., Unruh, G., & Ürge-Vorsatz, D. (2016). Carbon lock-in: types, causes, and policy implications. Annual Review of Environment and Resources, 41, 425-452.

Shove, E., & Walker, G. (2014). What is energy for? Social practice and energy demand. Theory, Culture & Society, 31(5), 41-58.

Shove, E., & Walker, G. (2014). What is energy for? Social practice and energy demand. Theory,

This project has received funding from the *European Union's Horizon 2020 research and innovation programme* under grant agreement No *837089*.

Culture & Society, 31(5), 41-58.

Sims R., R. Schaeffer, F. Creutzig, X. Cruz-Núñez, M. D'Agosto, D. Dimitriu, M.J. Figueroa Meza, L. Fulton, S. Kobayashi, O. Lah, A. McKinnon, P. Newman, M. Ouyang, J.J. Schauer, D. Sperling, and G. Tiwari, 2014: Transport. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

SLoCaT (2018). Transport and Climate Change Global Status Report 2018. Available at: http://slocat.net/tcc-gsr

Sorrell, S. (2015). Reducing energy demand: A review of issues, challenges and approaches. Renewable and Sustainable Energy Reviews, 47, 74-82.

Staffell, I. L., & Bossmann, T. (2015). The Shape of Future Electricity Demand: Exploring Load Curves in 2050s Germany and Britain.

Staffell, I., & Pfenninger, S. (2018). The increasing impact of weather on electricity supply and demand. Energy, 145, 65-78.

Stavrakas, V., & Flamos, A. (2020). A modular high-resolution demand-side management model to quantify benefits of demand-flexibility in the residential sector. Energy Conversion and *Management*, *205*, 112339.

Steinbach, J. (2016): Modellbasierte Untersuchung von Politikinstrumenten zur Förderung erneuerbarer Energien und Energieeffizienz im Gebäudebereich. Fraunhofer Verlag. ISBN 978-3-8396-0987-3

Swan and Ugursal, 2009. Modeling of end-use energy consumption in the residential sector:

TRT (2018). TRT TRASPORTI E TERRITORIO. DESCRIPTION OF THE TRUST MODEL. http://www.trt.it/wp/wp-content/uploads/2016/09/TRUST-model-detailed-description-1.pdf

Ürge-Vorsatz, D., Cabeza, L. F., Serrano, S., Barreneche, C., & Petrichenko, K. (2015). Heating and cooling energy trends and drivers in buildings. Renewable and Sustainable Energy Reviews, 41, 85-98.

Ürge-Vorsatz, D., Cabeza, L. F., Serrano, S., Barreneche, C., & Petrichenko, K. (2015). Heating and cooling energy trends and drivers in buildings. Renewable and Sustainable Energy Reviews, 41, 85-98.

Ürge-Vorsatz, D., Rosenzweig, C., Dawson, R. J., Rodriguez, R. S., Bai, X., Barau, A. S., ... & Dhakal, S. (2018). Locking in positive climate responses in cities. Nature Climate Change, 8(3), 174.

Van Beeck, N. (2000). Classification of energy models. Tilburg University, Faculty of Economics and

Business Administration.

Van Benthem, A., & Romani, M. (2009). Fuelling growth: what drives energy demand in developing countries?. The Energy Journal, 91-114.

Wang, H., Chen, W., & Shi, J. (2018). Low carbon transition of global building sector under 2-and 1.5-degree targets. Applied energy, 222, 148-157.

WEO'06 – established by The International Energy Agency (IEA), published as "World Energy Outlook 2006" in 2006. The World Energy Model (WEM) was expanded for the WEO-2006.

Worrell, E., Ramesohl, S., & Boyd, G. (2004). Advances in energy forecasting models based on engineering economics. Annu. Rev. Environ. Resour., 29, 345-381.

Zhang, R., Fujimori, S., Dai, H., & Hanaoka, T. (2017, June). Modelling Transport Energy Demand and Emissions: Development of a Global Passenger Transport Model Coupled with Computable General Equilibrium Model. In Meeting the Energy Demands of Emerging Economies, 40th IAEE International Conference, June 18-21, 2017. International Association for Energy Economics.