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Energy demand science for a decarbonized society in the context of the residential sector

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ABSTRACT

To develop a decarbonized society, two contradictory requirements must be met: (1) reducing energy demand and (2) creating flexibility in energy demand in order to respond to fluctuations in renewable electricity generation. To help meet these requirements, conventional energy efficiency studies should be extended to incorporate "energy demand science." This paper presents a definition of "energy demand science" and then reviews the related history and research questions of energy demand science in the context of the residential sector. It then examines three key areas that must be integrated into the next-generation energy demand science: (1) energy demand measurement with detailed granularity and analysis using cutting-edge technology, (2) energy demand modeling that helps clarify the formation mechanism of energy demand, and (3) identification of the factors that influence people's decision making, which represents typical human-dimension research.

Energy demand science consists of technical, human, natural environment, demographic, and land-use dimensions, and their integration is key for the establishment of a decarbonized society.

1. Introduction

To achieve the decarbonized society envisioned by the Paris Agreement and the Intergovernmental Panel on Climate Change (IPCC) special report on the impacts of a global warming of 1.5 °C [1], further energy demand reductions are becoming increasingly important. To ensure significant progress in energy demand reduction, it is essential to develop a deeper understanding of the mechanisms that determine energy demand at every level. For the residential sector this deeper understanding must include occupant behavior and lifestyle, appliance efficiency, equipment efficiency, building energy efficiency, the selection of energy sources, and the integration of all these factors.

Conversely, effective power system management is required to achieve the efficient distribution of renewable electricity. For a power system that includes a large share of solar photovoltaics (PV) and wind, as well as battery and power-to-gas systems, energy demand must be flexible, so it can accommodate fluctuations in the renewable power supply. Progress in Internet of Things (IoT) technology has made it possible to instantaneously control the operation of potentially millions of appliances in response to grid requirements. Thus, a fundamental energy challenge in this century will be to reconcile the conflicting requirements involving the simultaneous reduction of energy demand while ensuring flexibility.

To solve this problem, a deeper scientific understanding of energy demand is needed. While energy supply and distribution systems can be modeled by physical laws, understanding energy demand requires the establishment of a new interdisciplinary scientific field that incorporates physics, architectural/mechanical/electrical engineering, information science, behavioristics, economics, the humanities, sociology, and more. The authors propose to call this interdisciplinary research field "Energy Demand Science."

Extensive review papers have been published related to these areas; however, these reviews usually cover a specific domain or issue. This paper provides a comprehensive understanding of the areas of energy demand science as a framework of knowledge to solve energy demand related issues. We focus on the residential sector because of the significant impact of the human dimension (such as the effects of occupant behavior) and because it demonstrates the importance of

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interdisciplinary integration. The special contributions of this research are:

1) Presenting the two goals of energy demand for de-carbonization, reduction and flexibility, and formulating their conditions for de-carbonization.
2) Proposing the "reductionism approach" based on a mechanism of energy demand determination. As a distinctive research methodology, research on "energy demand measurement with detailed granularity" and "energy demand modeling" are reviewed.

This paper introduces the concept, approaches, and methodologies of energy demand science for application to residential sector energy demand, and reviews the related research.

2. Definition and background of "energy demand science"

2.1. Definition and history of energy demand science

In this paper, energy demand science is defined as: "The elucidation of the composition and behavior of energy demand such that it can be applied to the engineering planning, design, and operation of sustainable energy systems."

Energy demand science has its roots in the 1970s, following the first oil shocks. Before then, rising energy demand had been treated as an inalterable feature of a developing economy such that researchers have focused on strategies to supply the ever-increasing need for energy, such as Lovins' [2] so-called Hard Energy Path. In the mid-1970s, however, techno-economic studies of energy efficiency demonstrated that large reductions in energy consumption could be achieved with cost-effective investments. In 1975, the American Physical Society [3] explored the physical limits of efficiency improvements. By developing the concept of second-law efficiency, they demonstrated that large reductions in energy use were possible. Meier et al. [4] showed how the cumulative savings achieved through the widespread adoption of efficiency improvements could displace proposed energy-supply facilities, while doing so at a lower cost. Schipper and Lichtenberg [5] compared the energy efficiencies of the Swedish and U.S. economies and demonstrated that, across the board, Sweden extracted more energy services than the U.S. with no loss in quality of life (QoL). Finally, Lovins [2] outlined Soft Energy Path scenarios where a combination of increased energy efficiency and renewable energy sources could lead to an economy relying almost entirely on renewable energy. Considering the relationship between energy services and energy demand, Nakagami [6] investigated the changes in people's living environment and lifestyle and the energy consumption of Japan's residential sector until the 1990s in detail. As a result, although the energy consumption of the Japanese residential sector was lower than that of Europe and the United States, Nakagami predicted that it would increase in the 2000s. This increase was predicted because Japanese homes, which provided poor thermal comfort in the winter, would gradually adopt indoor temperatures closer to those in Europe and North America.

Through these and many other studies, a deeper understanding of energy demand and the potential role of increased efficiency evolved. However, most energy efficiency studies focused on a single element of the whole system, such as a building, appliances within the building, or modifications to occupant behavior. This approach typically relied on a single scientific discipline and did not incorporate the comprehensive structure of energy demand. Alternatively, overall energy demand has been modeled as a very simple function, without considering the actual internal processes that occur, because the whole mechanism of energy demand is too complicated to be modeled correctly. For example, the national scale annual energy demand is usually modeled as a function of a macroscopic index such as GDP and population [7]. This relationship is based on historical relationships. However, after the Great East Japan Earthquake of March 2011, the Japanese industrial, commercial, and residential sectors succeeded in drastically reducing energy demand, and that reduction persisted for almost four years [8,9]. This was independent of GDP growth, as shown in Fig. 1. Because decoupling economic growth from energy demand is one of the important objectives for decarbonization, the relationship between GDP growth and increased energy demand will not be valid in future modeling.

In many studies of energy management for buildings or communities [11,12], daily or hourly energy use is forecasted by a time-series analysis that relies on a few explanatory variables such as outdoor air temperature. However, these methods are not capable of predicting changes caused by consumer behavior or demand programs that are now being promoted by many utilities.

Given the state of demand models such as those described above, novel energy research will be required to further elucidate the mechanisms of energy demand. Creutzig et al. [13] proposed a transdisciplinary approach to identify demand-side solutions to mitigate climate change. Their approach includes technology choices, consumption, behavior, lifestyles, coupled production-consumption infrastructures and systems, service provision, and associated sociotechnical transitions. This is in fact the energy demand science approach we advocate.

Before reviewing the methodology of energy demand science, the following subsections explore some of the key research questions it must address:

1. How can we determine the minimum energy requirement necessary to achieve a decarbonized society?
2. How is flexible energy demand to be satisfied by carbon-free energy?
3. What mechanism determines energy demand?

These questions focus on modeling and forecasting energy demand because they illustrate the transdisciplinary aspects that will be required.

2.2. Minimum energy requirement for a decarbonized society

The Kaya Identity [14] is often used as a starting point for analyzing emission drivers by decomposing overall changes in GHG emissions into underlying factors [15].

$$CO_2Emission = \frac{CO_2Emission}{Energy\ Demand} \times \frac{Energy\ Demand}{GDP} \times \frac{GDP}{Population} \times Population \tag{1}$$

This decomposition makes it possible to observe, manage, and plan for the entire mechanism of carbon dioxide (CO_2) emissions. However, when considering the implementation of decarbonization, the Kaya identity is less valuable. The first term expresses the carbon intensity of energy. Because this term must be zero, the interpretations of the subsequent terms become nonsensical. To investigate the role of energy

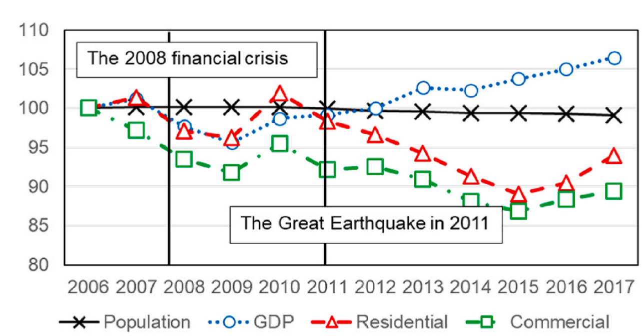

Fig. 1. Changes in energy use, GDP, and population in Japan (2006 = 100) [10]. After the Great East Japan Earthquake of 2011, Japanese energy demand in the residential and commercial sectors decreased despite the increasing GDP.

demand reduction for decarbonization, this equation should be transposed to express the balance between the amount of carbon-free energy and energy demand. Other adjustments are also needed. Considering the residential sector, it seems appropriate to substitute GDP with the service produced by energy use and the occupant's welfare, well-being, or QoL (the ultimate goal of energy use), which is reffered to as "sufficiency" in this paper. Finally, the energy demand must satisfy the following constraint for each energy service:

$$\textit{Amount of carbon-free energy} \geq \frac{\textit{Energy Demand}}{\textit{Service}} \times \frac{\textit{Sevice}}{\textit{Sufficiency}} \times \frac{\textit{Sufficiency}}{\textit{Population}} \times \textit{Population} \tag{2}$$

The first term on the right side denotes energy efficiency, which is a technical dimension. Because energy demand is "derived demand," it can be said that the service is the actual occupant demand. The second term expresses the quality and effectiveness of a service. Nørgård [16] called the relationship between energy service and occupant welfare "lifestyle efficiency" and noted that constraints for the lifestyle and diversity of cultural values should be considered when implementing energy savings achieved by lifestyle changes. The third term is the degree of satisfaction or quality of life per person. Additionally, the product of the second and third terms represents a per-person service, which shows the effects of service sharing. Note that the second and third terms belong to the human dimension.

To determine the required amount of carbon free energy, it is necessary to quantify the minimum energy requirements that provide sufficiency. However, the concept of "sufficiency" remains controversial. Grubler et al. [17] proposed a low energy demand (LED) scenario, where global energy demand in 2050 is 40% lower than the current level and meets the 1.5 °C climate target without relying on negative emission technologies. The LED scenario has five main drivers of long-term change in energy end use: quality of life, urbanization, novel energy services, end-user roles, and information innovation.

These investigations show that it is necessary to integrate both technical and human dimensions to create a formulation of energy demand that can characterize a decarbonized society. This paper reviews measurements and analysis of energy demand data and energy demand modeling to illustrate the technical dimension and it reviews factors influencing the pro-environment behavior to illustrate the human dimension.

2.3. Energy demand management when energy supply fluctuates

When on-site renewable energy is widespread, effective energy management is necessary to coordinate the energy supply from renewable energy sources (which are inherently variable), electricity from a nationwide electricity system, and fluctuating energy demand. The use of a smart grid [18] and demand response as an element [19] will optimize these elements in each building/house/community to produce overall system optimization.

Cutting-edge studies on energy demand underpin an energy management system (EMS) that disaggregates energy demand to the appliance level at a high time resolution and classifies it into flexible demand and other forms [20,21]. This type of EMS clarifies the relationship between changes in flexible demand and the degradation of an energy service. Since an energy management system usually concerns a small number of buildings, the variation of energy demand in each house/building must be considered. A high-resolution demand model, including both space and time, is needed to predict the electricity load curve and simulate electricity distribution lines. In the residential sector, a human-centric approach that includes factors such as occupant behavior and acceptance of demand response is important. Equation (2) must be satisfied at all time steps.

The EMS design and decarbonization must be considered simultaneously, because energy demand will become less flexible and renewable electricity supply will become more unstable in a decarbonized society.

2.4. Mechanism of energy demand determination

One of the important challenges of energy demand science is disaggregation of energy demand. Daly [22] said: "Who is going to require the energy? How much energy? What kind of energy? For what purpose? For how long?" The answers to these questions are important for prioritizing energy demand and for efficient energy management. Conversely, there is also a research method used to clarify the mechanism of occurrence for each energy demand and to construct a bottom-up type model. It also involves clarifying the mechanism of energy demand changes related to weather conditions, demand response signals, and other factors using the model. Fig. 2 shows the mechanism of energy demand determination in residential buildings. In the real world, only appliances consume energy. The actual energy consumption of an appliance is determined by the appliance's on-off status, its energy efficiency (specification of appliance), and the load on the appliance (its service requirement). These factors are affected by the behavior and preference of the occupants, weather conditions, the energy efficiency of the appliance/building, and so on. In addition, because energy demand is a "derivative demand," it is important to identify the energy service actually consumed by the occupant. The relationships among consumed energy service, occupants' lifestyles, and their sufficiency (well-being, welfare, QoL) must also be identified in order to clarify the energy service that is necessary to maintain the occupants' sufficiency. Investigation of these mechanisms comprises various dimensions, described below.

The Human dimension is unique in demand-side energy systems. For residential buildings, one must consider the occupants' time use, switch-on/off behavior, use of windows/curtains/blinds [23], appliance/building ownership, and the relationship between energy service and welfare. Steg et al. [24] showed that a sustainable energy transition must include the adoption of energy efficiency measures in buildings, the adoption of energy efficient appliances, and changing user behavior to reduce total energy demand. Royson et al. [25] showed that energy demand is formed by both energy policy and non-energy policy. The price of energy is just one aspect that influences behavioral changes. Research by Allcott [26], for example, demonstrated the extent to which norms also affect occupants' behavior.

The technical dimension has a long history in energy efficiency research, and it includes appliance and equipment energy consumption mechanisms during operation and stand-by, heat and air transfer in buildings, sensing and remote control of appliances, and so on.

The Natural Environment dimension explores the relationship between weather conditions and energy demand—not only the heating/cooling load, but also the effect of weather conditions on occupant behavior such as out-of-house activities.

The Demographic and Land-use dimensions are also important in residential energy demand. The number of households, which is determined by population and the average number of household members, has a major impact on energy demand in the residential sector. The

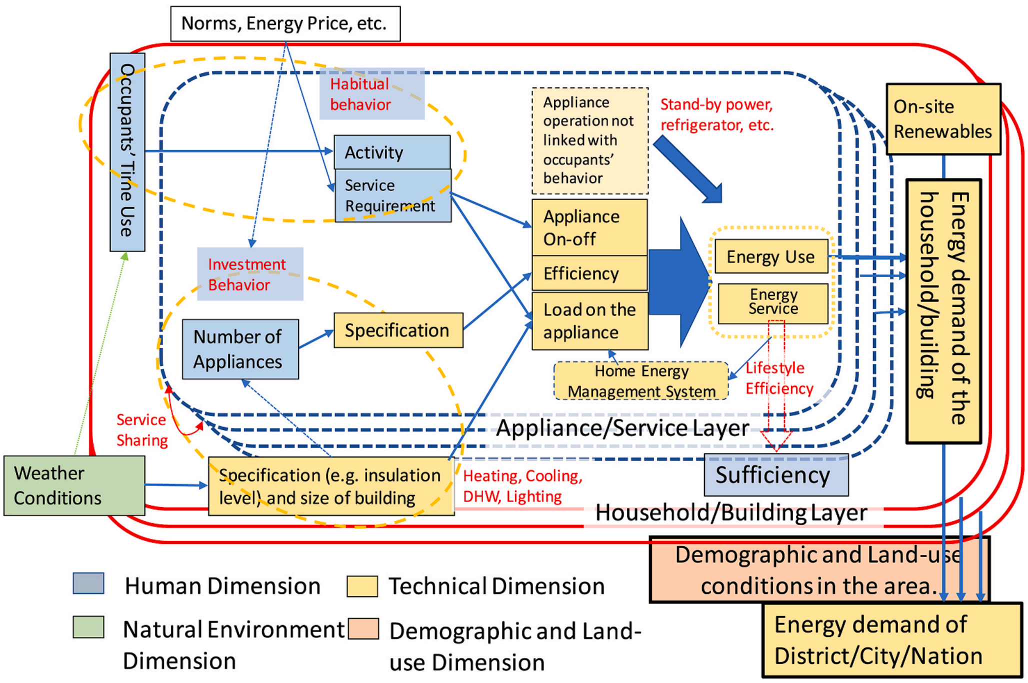

Fig. 2. Mechanism of energy demand determination. This diagram reproduces the actual process for determining the energy demand of a household as faithfully as possible. The energy consumption of a household consists of various kinds of appliance energy uses (each blue dashed line). Each appliance's energy use is determined by various factors that belong to the human/technical dimension such as the occupants' various behaviors, appliance specifications, and weather conditions in the case of heating, cooling, Domestic Hot Water (DHW), and lighting. The energy use of each appliance provides "energy service", and it contributes to the occupants' sufficiency. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

composition of the housing stock—which, when treated geographically, translates into land use—also affects energy consumption. These factors range from the proportion of apartments versus detached houses to their size, construction design, and materials.

Energy demand science incorporates the element reductionism approach, as shown in Fig. 2, but a holistic approach may also be possible. A holistic approach, such as machine learning, does not use disaggregation; instead, it treats energy demand as a black box model, because the mechanism of energy demand change is a complex system that cannot be modeled as an aggregate of individual elements.

In the case of demand response, reductionism is useful in the planning of automated demand response systems and in discussions of the relationship between energy use and service/comfort. It has developed most recently as a result of progress in IoT. On the other hand, the holistic approach hypothesizes that energy demand is too complex to model as a system of elements. In this sense, it is appropriate to examine manual demand response [27]. It can be argued that excess reductionism degrades prediction accuracy, which suggests that a hybrid of the two approaches is needed.

2.5. Importance of discipline integration for energy demand science

Numerous studies have been conducted on each dimension of the reductionist approach, as well as on the holistic approach. However, to respond to the future requirement of decarbonization, it is necessary to conduct research that addresses the entire structure of energy demand, as shown in Fig. 2, from a higher perspective. Additionally, in the holistic approach, possessing background knowledge for each dimension is indispensable in creating a research plan and interpreting results. In other words, an interdisciplinary energy demand science is required that integrates and merges technical, human, natural, demographic, and land-use dimensions, while also investigating energy demand from both reductionist and holistic perspectives simultaneously. At the same time, it is important to increase the ability of researchers to conduct such interdisciplinary research. Reducing energy demand by one unit is equivalent to increasing energy supply by the same amount (and the ratio may exceed one if there are losses during transformations). However, in general, reducing demand is easier because the energy supply system basically depends only on the technical dimension.

Schmidt and Weight [28] insist upon the importance of interdisciplinary energy research between economics and social science for reducing energy demand. However, energy demand research requires knowledge of natural science, and interdisciplinary energy research is necessary for the flexibility of energy demand as well as energy demand reduction.

3. Research areas of next-generation energy demand science

Although extensive research related to energy demand science has been conducted, the following three areas are considered to be the key issues that must be integrated into next-generation energy demand science: (1) energy demand measurements with detailed granularity and analysis using cutting-edge technology; (2) energy demand modeling that helps to clarify the formation mechanism of energy demand, and (3) identification of the factors influencing people's decision making, which is a typical human-dimension research area. Key papers and research themes related to these topics are reviewed below.

3.1. Measurement and analysis of energy demand data

The popularization of smart meters and the progress of IoT technology has greatly lowered the cost of data acquisition, which has permitted a large increase in the number of studies collecting and analyzing large-scale data. The purpose of an energy demand analysis is to clarify both the values of the elements shown in Fig. 2 and the correlation among the elements. The analysis results will provide useful information for energy demand forecasting, energy efficiency policies, and energy management. In addition to measuring the energy consumption of an entire house using smart meter data, it is also possible to measure the detailed energy consumption of each piece of equipment using a home energy management system or an IoT device. Items other than energy, such as temperature and occupant behavior, can also be measured.

There has been a significant amount of research on smart meter analysis over the last decade. Yildiz et al. [29], reviewed methods and techniques for using smart meter data such as forecasting, clustering, classification, and optimization. They described various applications for customers and utilities. Additionally, Glasgo et al. [30] reviewed technological and analytical methods using granular data on residential energy use collected mainly in the United States. In this section, we focus on residential smart meter data analysis, which is generally likely to be implemented, and we review three areas of analytical methodology. We used the Google scholar engine to search for literature in this field. Phrases that are related to the analysis of electricity demand data in the residential sector were employed to identify relevant literature. First, review papers after 2015 were identified using search phrases such as "smart meter data" plus "review", and "residential electricity" plus "review". Next, phrases including "smart meter data analysis", "smart meter data classification", "residential (domestic) electricity determinants", "residential (domestic) electricity factor", "residential electricity classification", "residential electricity disaggregation" and "non-intrusive load monitoring" were reviewed.

3.1.1. Clustering and classification

The applications of clustering smart meter data include the understanding of consumer characteristics, examination of energy saving potential, determination of effective tariff structures and demand response programs, and so on. For example, households that demonstrate consistently high demand in the evening may be candidates for installing storage devices. The correlation analysis between household attributes and the cluster feature index may aid in the estimation of new customer load profiles.

There are two forms of clustering based on usage patterns of power data. One involves the classification of a plurality of consumers into similar groups, and the other classifies the daily load profiles into the similar usage patterns of one customer to estimate their behavior. There are analysis methods suitable for each clustering method. Yildiz et al. [29] reviewed clustering techniques; data specifications such as the number of consumers, data acquisition period, time interval, etc.; and clustering validity indices in 15 research groups. Methodologies for technical clustering methods and clustering validation have been periodically reviewed [31–33]. Tureczek et al. [34] conducted structured literature reviews related to research in electricity customer classifications using smart meter data and identified 34 significant papers. They noted that there is a lack of consideration of applications, correlation analysis between time series, and detailed descriptions regarding the treatment of missing values.

3.1.2. Impact analysis of energy demand determinants

It is possible to estimate energy demand in the future or in unknown regions without energy information by clarifying the relationship between energy consumption and socioeconomic-, building-, and appliance-related factors. Many impact analysis studies have been conducted in which analyses such as regression were performed with the annual energy consumption as the objective variable and socioeconomic-, building-, and appliance-related factors as explanatory variables. Jones et al. [35] reviewed evaluation studies of factors affecting household electricity consumption, and organized the impacts of more than 62 factors, including 13 socioeconomic factors, 12 housing factors, and 37 equipment factors. They found that four of the socioeconomic factors, seven of the dwelling factors and nine of the appliance-related factors had significant positive effects on electricity use. Determinants were also analyzed using high-resolution data provided by smart meters and home energy monitors, as well as factors that indicate demand characteristics such as peak demand and demand by season or time zone [36–38].

Conversely, machine learning techniques were also studied to automatically estimate specific attributes or behaviors of a household using its electricity data. Beckel et al. [39] created a classifier from the relationship between household attributes and electricity data from the smart meter data of 4232 households in Ireland, at a 30-min granularity over a period of 1.5 years. Their classifier could estimate the index reflecting a household's at-home situation, the number of people, and the number of home appliances with relatively high accuracy. In addition, Anderson et al. [40] built a logistic regression model of indicators and attribute data that showed the characteristics of demand and estimated the employment status of householders. Jin et al. [41] created a classifier with high accuracy, using various machine learning methods to estimate the at-home situation from the demand data in commercial and residential buildings, and also proposed a classification method for use when the learning data are limited.

Estimating consumer behavior and attributes from energy data enables the utilization of energy information for purposes other than energy, such as monitoring services for elderly people or marketing businesses. It leads to the improvement of customer satisfaction and additional incentives to maintain energy data acquisition.

3.1.3. Non-intrusive load monitoring

Non-intrusive load monitoring (NILM) technology is a method of disaggregating the total household electrical load measured at a single point into individual appliance signals. The NILM concept proposed by Hart [42] in 1992 has been studied for a long time, and many machine learning methods have been proposed. Armel et al. [43] reviewed disaggregation algorithms and their requirements and evaluated the extent to which smart meters can meet those requirements. Esa et al. [44] discussed the benefits of appliance-level data and reviewed disaggregation algorithms and their requirements. They also evaluated whether the technical specifications of smart meters are adequate to support the algorithm requirements. Hosseini et al. [45] analyzed NILM applications from the stakeholders' perspectives, and noted that traditional application of NILM for energy auditing, which uses only electricity consumption data, has reached its limits in terms of accuracy. They insisted that advanced NILM should focus on deferrable/thermostatic appliances such as electric water heaters, and space heating/cooling systems, because their specific advantages can provide flexible power resources. Recently, a general research method that relies solely on smart meter data to decompose electricity consumption is becoming more popular. The service of disaggregating smart meter data has already been commercialized, leading to a rich information supply for customers.

The demand analysis approaches described above are useful to improve the accuracy of reductive models. Fig. 3 shows the structure of the available data and analysis methods, and their application in the residential sector. Many tools for quantitatively evaluating the effects of energy management based on demand side data have been developed [46], and in the future it will become essential to provide reliable information to customers based on convincing demand data.

3.2. Energy demand modeling

Energy demand models have been developed for various purposes: understanding and estimating the current status of energy demand and future changes; identifying the effect of options to change energy demand; and identifying, framing and prioritizing options and decisions [47–49,53]. Several reviews have been undertaken though, again, generally from the perspective of a single discipline. In this section, we summarize review papers related to the energy demand modeling to identify the development and challenges as a method of the energy demand science.

To search for the relevant review papers, we used the Web of Science with the retrieval key of "building" AND "energy demand" AND "modeling" AND "review." As a result, we found 65 review papers published in peer-reviewed journals. After reading the papers, 51 relevant papers were finally selected.

3.2.1. Overview of the selected review papers

The largest group of the selected papers were related to the modeling techniques [56–60,99] with a variety concerning temporal resolution including time series forecasting [61,98] and load curve modeling [49, 50], as well as spatial scale including urban-level [48,51–55,62,108],

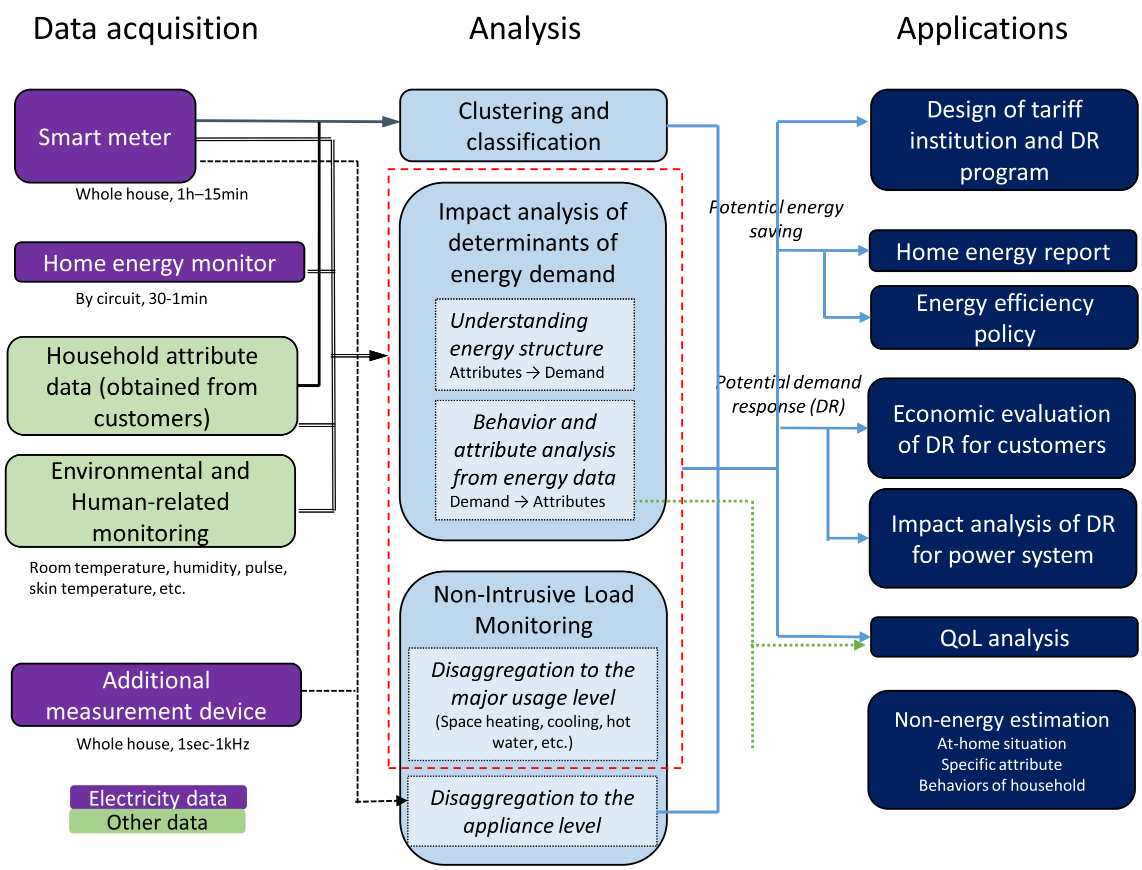

Fig. 3. Structure of the available data and analysis methods and their applications in the residential sector. The items in purple are electricity consumption data by resolution, the items in green are attribute data that are linked with electricity data, the items in light blue are the demand analysis methods described in section 3.1, and the items in dark blue are the applications obtained via analysis. The realization of energy conservation and demand response while maintaining the QoL of consumers in the residential sector requires ease of data utilization and detailed analysis, as shown in the figure. The comprehensive collection of electricity consumption data is not yet sufficient; the figures assume the future construction of a platform for data utilization, improvement of analysis methods for each application, and the expansion for commercialization. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

district/neighborhood-level [63,64], and cluster-level [66]. The other papers can be classified by research domains in which energy demand data is used: including building design [65], building control and operation [57], home and building energy management [67–72], community energy planning [73], building and distributed energy systems' design [74–76], the analysis of energy systems [47,77], electricity systems [103], demand response, and demand flexibility [78,79]. A smaller group of papers deal with modeling uncertainty by incorporating methods for analyzing uncertainty and calibrating parameters [80,111], as well as by developing models of key drivers and elements of energy demand including those associated with occupant behavior [81–84,106, 107] and meteorological conditions [85–89]. Fig. 4 shows the overview.

3.2.2. Existing modeling approaches

Modeling is defined as the construction of models that represent systems. Rosen [90] describes models as a "formal system," whereas the modeled system is referred to as the "natural system" [91]. The natural system is a system that determines building energy demand, which is illustrated in Fig. 2. The factors that directly determine appliance energy consumption are those related to the user's need for a service, the user's appliance use behavior, environmental conditions, the building and house, and the specifications of the appliances. For example, the energy demand of a household is shaped by the daily activities of household members, the use of appliances involved in those activities, the possession and specifications of appliances, the specifications of the house, and the outdoor environmental conditions. In the theory of social practice, people's everyday practices are shaped by material elements (appliances, house, and other artifacts), social and cultural meaning, and the knowledge necessary to participate in such practices [92]. These elements are shaped by the systems of everyday practice, including the media, the internet, and the systems that produce and supply appliances [93,94]. Demographic conditions and housing also are shaped by the social environment, including culture, norms, national policies, and service sectors for housing, childcare, and education [95]. Due to the structures of those systems, each household has a unique energy demand. These systems have interactions with the national/global economy and social systems, causing the natural system of energy demand to be complex and hierarchical.

The reductionist approach deals with the system structure on a deeper level, considering the direct determinants of energy demand, whereas the holistic approach focuses on an aggregated quantity and behavior associated with the demand. In the energy demand modeling field, energy demand has been quantified at the level of (A) appliance, (B) building, and (C) building stock. For any level of quantification, the modeling methods generally can be classified into those that are data-driven and those that are theory-driven [80]. Both modeling methods can be applied in both the reductionist and holistic approaches. The Kaya decomposition method is an example of a data-driven model based on the holistic approach. A reductionist approach can be applied to quantify the energy demand of a household by summing up the energy consumption of all appliances quantified based on both data-driven and theory-driven approaches.

Data-driven models use historical data showing the relationship between energy demand and the model inputs, to train the model to

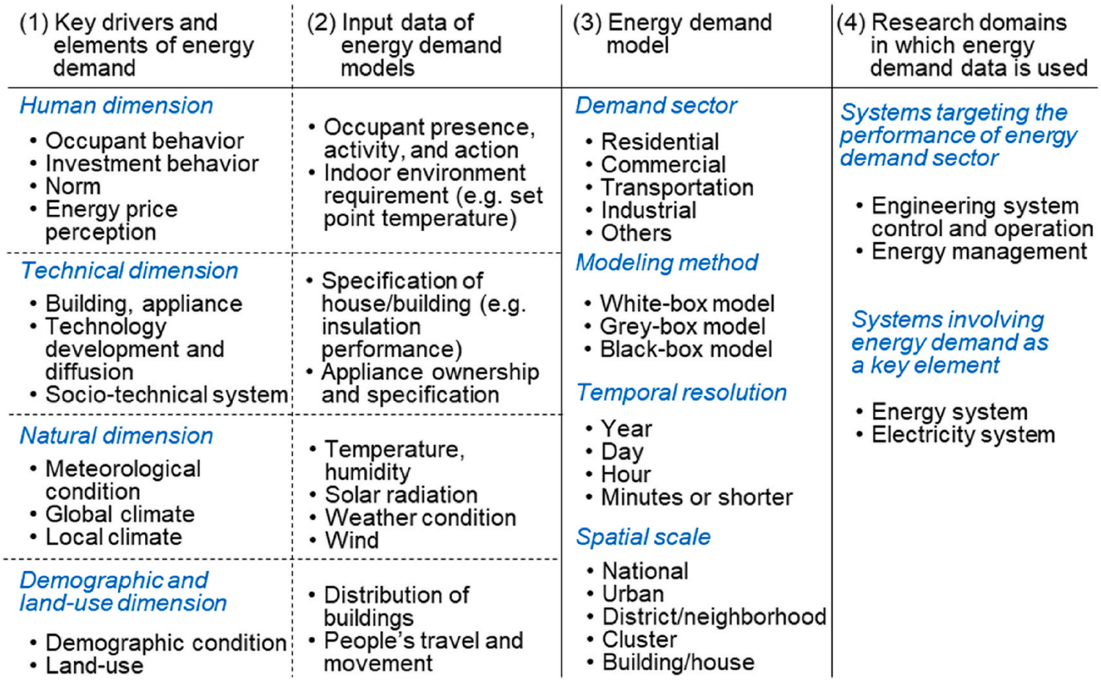

Fig. 4. Overview of energy demand models. The first column lists the dimensions listed in Section 2 and examples of key drivers and elements in these dimensions. The second column lists examples of input data given to an energy demand model related to the dimension. The third column lists energy demand models categorized by the sectors, modeling method, and spatiotemporal resolution. The fourth column lists the research domains in which energy demand data is used.

predict model outputs [96]. According to Wei et al. [97], artificial neural networks, support vector machines, statistical regression, decision trees, and genetic algorithms are the most frequently used data-driven methods used to predict building energy demand. Hybrid methods are also used [98]. The data-driven methods can be applied at the building stock level. Swan et al. [99] and Kavgic et al. [48] called data-driven models based on a holistic approach "top-down models." In the electricity system domain, data-driven methods have been used to predict electricity demand based on historical data [50]. The data-driven methods can be applied at the appliance level to model appliance electricity consumption. However, to address the influence of the user, the occurrence of switch-on events is often modeled based on historical data [84].

The theory-driven method considers the structure in which the energy consumption of appliances, buildings, and building stock is quantified. Models can be developed based on the theory-driven method without historical energy data, although historical data are usually used to validate the model and calibrate model parameters. Instead, the theory-driven method requires understanding the structure that determines energy demand. Such understanding is not necessary in the development of data-driven models. Building simulation software such as EnergyPlus [100], ESP-r [101], and DeST [102], which simulate natural environment dimensions, are examples of theory-driven models [80]. There are tools also available at the district level [63]. These models are also called physics-based models, as energy demand is quantified based on physical equations [96]. To model energy consumption of appliances, statistical representation of the users' behaviors has been considered [84,106,107]. In modeling the energy demand of building stock, Swan et al. [99] identified three methods using a physics-based approach, considering the influence of buildings' physical properties. The first method uses sample buildings. The knowledge gained with the sample buildings is extrapolated to the entire building stock. The second approach uses building archetypes representing a segment of building stock. The final approach is the population distribution method, in which the statistical distribution of the physical properties of buildings are constructed based on which energy demand of the buildings is quantified.

The general implications of the data-driven and theory-driven methods are as follows [52,53,57–60,64,80,96]:

- It is rare that the system structure determining energy demand, elements of the system, and the mutual relationship among elements is fully understood and that the data describing these aspects are available. Therefore, the accuracy of theory-driven models is typically not high. Conversely, data-driven models generally have higher accuracy than theory-driven models when historical data describing the relationship between energy demand and input factors are available.
- The accuracy of data-driven models deteriorates when the models are extrapolated to an external context that the historical data does not cover. Conversely, theory-driven models are more reliable in terms of extrapolation as far as the structure determining energy demand is applicable.
- Theory-driven models generally are capable of quantifying the direct influence of a change in an element of the system. On the other hand, data-driven models have such a capability only when the element is considered as an input datum. Additionally, the quantified effect includes both direct and indirect influences.
- Data-driven models are capable of dealing with non-technical elements, such as household income. In contrast, theory-driven models require the relationship between non-technical elements with elements that directly determine energy demand to account for the influence of non-technical elements.

Due to these features, data-driven models are useful when the accurate prediction of energy demand is needed, when the structure determining energy demand is not fully understood and data describing the structure is not available, and when rich empirical data are available. Theory-driven models are useful for quantifying the direct causal relationship between energy demand and elements of the system, as well as when empirical data are not fully available. To utilize the advantages of both data-driven and theory-driven models, hybrid models that integrate both modeling approaches are often used [53,80,96]. Based on the review of calibration methods, Coakley et al. [80] concluded that the approach of combining data-driven and theory-driven models has the potential to increase the usefulness and transparency and to extend the application of models.

3.2.3. Challenges in energy demand modeling

As discussed in the previous section, many useful modeling methods have been established. This section addresses challenges of energy demand modeling as a method of energy demand science based on the challenges addressed in the review papers.

(1) High spatiotemporal resolution modeling with a high disaggregation capability

The first challenge is the establishment of the capability of modeling high spatiotemporal resolution demand data and disaggregating it, which originates from the relationship between the third and fourth columns of Fig. 4 [48,49,67,73,78]. The demand for high spatiotemporal resolution energy demand data has been increasing in the research domains listed in the fourth column. Disaggregated demand is important to quantify the change and flexibility in energy demand. However, several papers recognize the limitation in this challenge [57,103]. To overcome this issue, more methodological development is needed.

(2) Capturing the influence and behavior of key drivers and elements of energy demand

The second challenge originates from the modeling of the relationship between the first, second and third columns of Fig. 4. A wide range of drivers and elements influence energy demand, such as meteorological condition [69,85], technologies used in buildings [71], and occupant behavior [52,81–84,104–107]. These drivers and elements can be given as fixed condition, by a scenario describing their changes, or modeled by complicated models based on both data-driven and theory-driven approaches. Although there has been considerable development as summarized in the review papers, their application in the building energy demand modeling is still limited by computational capacity and the inadequacy of data and understanding [48,49,83]. For example, occupant behavior has a complex nature, which requires a large compilation of data and computational resources. Occupant behavior depends on complex demographic and environmental conditions including well-being, lifestyles, and many other factors, but the behavior is still not well understood. In addition, pertinent data is not available especially when a model considers the response to interventions [56,68,78], the cooperative response and behavior [70,83] and the organizational management [72]. The same challenge exists for other drivers and elements (e.g. meteorological conditions [86–88], and technology choice [52,65,75]). To overcome this issue, more data and knowledge on key drivers and elements should be accumulated [70,72,74,78]. Several papers suggested establishing a platform on which collections of models can be evaluated through exchange of data so that collaborations among different domains can be conducted and state-of-the-art models are readily accessible [50,52,54,66,76,89].

(3) Integration of demand sectors

The third challenge is the vertical integration within the third column. The residential sector is one energy use sector, but it is not isolated from the commercial and passenger transport sectors [48]. Important dynamics cannot be solved without considering the interactions between these sectors. One solution is to use a data-driven approach to integrate the considered sectors [108]. However, to utilize the advantages of theory-driven models, the approach using “collections of models” mentioned above appears promising [54,63]. One example is to apply agent-based modeling, which simulates people’s activity and quantifies energy demand based on this activity [62,91]. Simulation platforms such as MATSim [109] and SynCity [110] have already been established [107] to accommodate agent-based modeling. However, such agent-based approaches have not been fully integrated into building energy demand modeling because of the large data and computational resources required. In addition, methods to integrate different types of data and models have not been established [62].

(4) Treatment of uncertainty

To overcome the first three challenges, a detailed description of the energy system is necessary. This might involve a large number of uncertain parameters. Tian et al. [111] described two approaches to address uncertainty in building energy demand modeling. The first is to adopt a forward propagation approach, in which distributions in energy demand arising from variation in the input modeling parameters are quantified. The second is called “inverse modeling” or “model calibration”, in which the distributions of unknown parameters are quantified based on measured energy demand data. These methods to address model uncertainty work well with static parameters but are more difficult to apply when parameters change dynamically [56]. Thus, more integrated methods should be established to deal with uncertain parameters. The limitations addressed in the reviewed papers [48,80] are that there is no established standard for calibration; models are generally over-specified with too many inputs and under-determined with too few validation points; the uncertainty in model outputs are rarely quantified; and the calibration process is not often well documented. The reviewers recommended the use of automated optimization methods that identify multiple solutions within a parameter space identified from a knowledge-base of templates of influential parameters.

(5) Prediction of energy demand using a long-term perspective

The most important feature of the theory-driven methods is that the change in energy demand can be quantified due to a change in an element of the energy system. This feature is very important when estimating the energy demand of a decarbonized society in the long-term future, in which various changes may occur (e.g. in socio-demographic structure, building area, technology dissemination and meteorological conditions) [73]. Methods depending only on data-driven approach might be ineffective for long-term forecasting and planning, as the application is beyond the region of interpolation. Conversely, the theory-driven methods are rarely capable of considering the macroeconomic factors that can be considered by data-driven methods. Boßmann et al. [112] established a hybrid method combining both modeling methods to predict hourly resolution electricity demand in the year 2050 considering the dissemination of emerging technologies and flexibility options. The demands of these emerging technologies are independently quantified based on a bottom-up approach [50,78,79]. More importantly, structural changes may occur in several domains at the same time. Such change-chains that may occur in energy and power systems should be captured and models should be able to providing the capability of analyzing transformative paths [77,133].

3.3. Factors influencing the pro-environmental behaviors of energy consumers

It is important to know the factors influencing the behaviors of energy consumers in order to promote pro-environmental behaviors that will result in achieving a sustainable decarbonized society. Moreover, understanding the relationships among factors and consumers’ behaviors is expected to provide the knowledge necessary to implement effective interventions, as well as to establish one of the fundamentals for energy demand science. In this section, we introduce previous studies that focus on these two topics. We used the Web of Science to search for review papers that are related to factors concerning pro-environmental behavior. A retrieval key such as "energy AND factor* AND (behavior change OR demand side management OR demand response)" was used. We selected the research field of energy fuels, environmental sciences, and environmental studies, to exclude unrelated fields, such as medicine or health care. Our target period was from 1900 to 2019. We chose the most cited paper from the search results as the most widely accepted paper.

3.3.1. Influencing factors

Frederiks et al. [113] identified the factors of energy saving behaviors in households (Table 1). The factors are categorized into individual factors and situational factors. The individual factors are further divided into socio-demographic and psychological factors. The situational factors are categorized into contextual and structural factors. It is challenging to clarify which factor is the most dominant, mainly because of the feasibility of investigation. More than 150 research papers, which Frederiks et al. [113] collected to make Table 1, have their own combinations of factors and there is no discussion about the contribution ratio of these factors.

(1) Socio-demographic factors

Socio-demographic factors are related to personal and social information, such as gender, age, income and so on [113]. Of the many possible socio-demographic factors, a few are considered to influence pro-environmental energy behavior [114]. For instance, household income is considered to be a primary factor of energy saving behaviors because high-income individuals can easily obtain energy saving products such as solar panels, a hybrid car, or a fuel cell product. Family is identified as another factor, because households with young children use more energy than single households [113,115,116]. Conversely, some studies show that age, gender, and education are not strongly related to energy saving behavior, but that more personal attributes are related to pro-environmental energy saving behaviors [113,117,118].

(2) Psychological factors

Psychological factors, such as knowledge, awareness, and social norms, are identified as fundamental factors that influence pro-environmental energy behaviors. Knowledge and awareness of environmental problems can trigger behavioral changes. However, some people do not act to save energy because of a lack of motivation or clear guidelines, even if they are aware of environmental problems [119,120]. This phenomenon is called the "knowledge gap." Some previous studies mention that the pro-environmental behaviors cannot be explained by only socio-demographic factors or psychological factors [121,122]. Complicated relationships are observed among psychological factors, socio-demographic factors, and pro-environmental behaviors.

(3) Contextual and structural factors

Contextual and structural factors are categorized as situational factors, such as a new law or policy, or changing prices or taxes. Several studies have reported that such institutional programs are not easy to implement because they require time and money, although they can promote critical improvements in terms of energy saving behaviors [123–127].

Table 1
Socio-demographic, psychological, contextual, and structural factors that may influence household energy consumption and conservation (Created by the authors based on Frederiks et al. [113]).

Category	Subcategory	Influential factors
Individual factors	Sociodemographic factors	Age, gender, education and literacy, employment status, socioeconomic status and income, household characteristics (e.g., size, type, life cycle stage), dwelling characteristics (e.g., age, size, condition, ownership), geographical location (e.g., urban/rural, climate zone).
	Psychological factors	Knowledge/awareness (e.g., perceived risk/threat), values, beliefs and attitudes, motives, goals and intentions, personal norms, perceived responsibility and sense of moral obligation, personality tendencies (e.g., altruism, self-efficacy, perceived behavioral control), group membership and normative social influence, other cognitive, affective and motivational influences.
Situational factors	Contextual and structural factors	Laws, regulations and policies, available technology, pricing (e.g., tariffs, rebates and subsidies), built environment (design and infrastructure), information, mass media and advertising, neighborhood factors (e.g., community spirit, cohesion), broader public norms and community expectations, sociocultural traditions and customs, other social, cultural, economic, political and legal influences in the environment.

3.3.2. Models representing the relationships among factors and behaviors

Several models describe the relationships between factors and energy conservation behaviors in households. Thøgersen and Grønhøj [128] proposed a model that can explain the relationships among energy saving behaviors, psychological factors (e.g., self-efficacy), and structural and contextual factors (e.g., social norms) by adapting social cognitive theory [129]. Stephenson [122] developed a model of behavioral changes concerning energy saving that represents the relationships among cognitive norms, material culture, and energy practices based on discussions of energy cultures, which consider cultures and lifestyles. Unsworth et al. [130] conducted a survey of office workers to develop a model of changes in the psychological stages of pro-environmental behaviors. They concluded that psychological factors such as aims, attractiveness, and a sense of accomplishment are considered to be primary factors. Heckhausen and Gollwitzer [131] constructed a model of action phase (MAP), which is composed of four action phases: re-decision, pre-action, action, and post-action. Bamberg [132] revised the MAP by including psychological factors such as personal norms, negative emotions, and perceived responsibilities.

As mentioned above, researchers have introduced several models of pro-environmental energy behaviors. However, further research is required because there is still room to improve these models through investigations of the relationships among the individual factors, situational factors, and pro-environmental behaviors of energy consumers.

3.4. Summary/discussion

As described in 2.1, energy demand science is defined as the elucidation of the composition and behavior of energy demand. As shown in 3.1, smart meters and other IoT devices enable us to measure residential energy demand with a high degree of granularity, disaggregate it into end-uses and clarify the impacts of energy demand determinants. Moreover, detailed time resolution data is indispensable when considering the ability to manage electricity balances between demand and fluctuating renewable energy sources.

Various energy demand models have been developed that cover important aspects of the structure that determines energy demand. These models are based on a white/grey/black-box modeling approach or developed as collections of models. The decarbonization challenge requires models to be capable of capturing, in a holistic way, the overall characteristics and behavior in the multiple time and space scales of energy demand. Models must also allow analysts and practitioners to observe the change and flexibility that can be made in energy demand and its composition by technical, policy and behavioral measures based on the reductionism view. The most important limitation identified in this review was in the integration of state-of-the-art models in such a manner. A promising direction recognized in previous review papers is to establish a platform on which collections of models that can be operated through exchange of data. In this way collaborations among different domains can be conducted and state-of-the-art models are available in a timely fashion. Applying these integrated models to the decarbonization challenge is especially challenging; this requires the capability to explore transformative paths, including structural changes, in several concurrent domains.

Most of the new challenges in energy demand modeling described in 3.2.3 have not been addressed comprehensively in previous studies [62, 99]. A hybrid application of measured data and energy model development is important for understanding energy demand systems. Tronchin et al. [133] proposed a forward and inverse modelling integrated workflow.

Factors influencing the pro-environment behaviors of energy consumers have been widely noted and other review papers have similar outcomes [134,135]. However, it is not yet fully understood which factors most strongly influence pro-environmental behaviors. Previous research has mainly focused on the holistic approach but the next generation of research into energy demand science should integrate the holistic and reductionist approaches in order to capture microscopic behavioral changes.

4. Conclusions

This paper proposes the concept of energy demand science as a means of formalizing the complex methods required to model future energy consumption and carbon emissions, based on a review of previous and ongoing research activities. The insights obtained in this paper are as follows:

- To achieve a decarbonized society, there is a need to design an energy demand framework that reconciles two contradictory requirements: reducing energy demand, and creating flexibility in energy demand despite fluctuations in renewable electricity generation.
- Simple black-box models cannot elucidate the relationships between technology, behavior, and the environment; as a result, traditional models may be incorrect to such an extent that even the sign of change is wrong. Future models must consider the increasing interactions between intermittent energy supplies, human behavior, and the context of a particular energy system.
- The integration of technical, human, natural environment, demographic, and land-use dimensions is the key issue for energy demand science and for the establishment of a decarbonized society. A more comprehensive understanding of the mechanisms that determine energy demand is needed.
- Currently, energy demand measurements and models are limited to those aspects that can be quantified. However, the requirement for achieving a decarbonized society described by Equation (2) implies that a better understanding of the human service demand is required. Advances in IoT and data analysis techniques in measurements, as well as modeling methods considering human behavior, would contribute to better understanding of the service demand.
- The integration of measured energy demand data and theory-driven modeling is expected to greatly contribute to the elucidation of mechanism that can determine energy demand. An adequate number of tools are available to analyze energy demand; however, for these tools to contribute to the realization of a decarbonized society, research must be structured to use these tools in the desired direction.
- Defining, measuring, and balancing the "proper" indicators of value for the supplier, customer, system, and environment is a significant research agenda. For example, the customer's goal is not to use energy but to improve their quality of life (QoL) through that energy use. Therefore, a customer's QoL may be a more proper indicator, rather than the energy usage itself.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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