The Potential and Limits of Digital Energy Advisors

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***Abstract*—Information asymmetry between building owners and suppliers of sustainable building renovations threatens to slow the energy transition. This study introduces the concept of a Digital Energy Advisor (DEA) which autonomously and transparently provides personalized guidance in an educational way about the technical, economic, and environmental aspects of sustainable buildings. The technical requirements of building a DEA are described, including model structure and input data, which connects to the barriers found in being able to realize such a tool available to the public. It is shown that while it is technically possible, data procurement costs, personal privacy via GDPR, and the intellectual property of private firms establish the limits for creating a non-profit, publicly accessible DEA. Technical and commercial pathways around the barriers are discussed, and the conclusion is that an open-source business model has the greatest potential for a public DEA.**

Keywords—Information asymmetry, urban building energy model, consumer education, data protection, GDPR

I. Introduction

The timing of the COVID-19 pandemic, shuttering of nuclear plants, and removal of Russian natural gas have all been catalysts towards a top-down reimagination of Europe's energy systems. The EU's Green Deal consists of several investment programs, e.g. Renovation Wave, Taxonomy for Sustainable Activities, and REPowerEU, that all rely on renovations to building energy systems [1]. The owners and users of these buildings are therefore key stakeholders in the energy transition, and the decisions they take will greatly influence the development of our urban, national, and international energy infrastructure.

The geopolitical situation in Europe has accelerated the energy transition as building owners seek to increase energy security through local renewable sources and protect themselves from high energy costs. The rapid adoption of solar photovoltaics (PV), batteries, and electric vehicles (EV) is considered positive and necessary for the energy transition [2], however a "gold-rush" situation is forming where providers are selling the trendiest sustainable energy products as fast as they can [3]The complexity around energy systems and sustainability makes it difficult for consumers (and sometimes even experts) to make optimal decisions, especially given the abundance of media in everyday life that can send simple but conflicting messages [4], [5].

Many publicly available digital tools already exist for planning and control of building energy systems from commercial and non-commercial sources. However, they tend to either have educational aspects or personalized aspects, but not both [6]. Given the potential benefits of freely available, educational, and personalized information about sustainable building energy renovations, this paper is an exploratory study into the potential for digital energy advisors (DEA), which are capable of automatically guiding building owners towards sustainable renovations without technological bias or sales pressure. It includes a state-of-the-art review of current simulation technologies, input data requirements, barriers to development, and potential pathways forward. The material is based on the direct experiences of the authors in constructing high spatial and temporal resolution urban energy simulations via three research projects [7], [8], [9]. There is an increased interest in such models and the lessons learned and documented in this study will be of value to others currently working in the field and those looking to move into it.

The structure of the paper is as follows; following a brief background on information flows in building energy systems, a more complete description of a digital energy advisor is given to establish a goal for what could or should be built. Next is a state-of-the-art review of the digital tools for building a DEA at scale and their respective needs for data. Categorically these tools are known as building stock models (BSM) or urban building energy models (UBEM) depending on the level of influence between buildings, and explicitly do not include transport systems beyond the charging of EVs at a building. The barriers to building a DEA are described next, and the paper concludes with a discussion of possible pathways for overcoming these challenges.

A. Background

Under economic liberalism, the best outcomes for a society can be achieved if individuals make rational, self-interested decisions with complete information within policies that represent the collective will of society. To have complete information requires two parts: first, that the information is available, and second, that the decision maker can make use of it. Information gathering is usually done through multiple channels which can be roughly grouped into three categories; non-commercial, commercial, and peers. These information channels are stylized in Fig.1 as part of the decision-making process informed by Rogers [10], and are colored yellow, blue, and red for non-commercial, commercial, and peer sources, respectively. A mixture of commercial and non-commercial information shows as green.

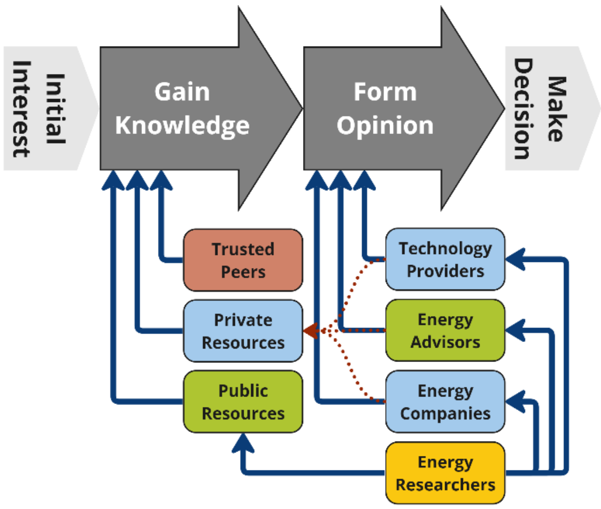

Fig. 1. Decision-making process with information channels. Yellow - non-commercial. Blue – commercial. Red – peer sources. Green – mixture.

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Non-commercial channels are those who are not connected to selling the technology, such as government advisors, academics, or non-governmental agencies. They aim to provide non-biased information to shape attitudes and norms around pro-environmental behavior, but is typically generalized for a broad audience. This includes reports and articles about technologies that both inform the public as well as public policy that help shape the energy system at large. Non-commercial information can be given on an individual basis, such as municipal energy advisors, who are available at no cost to ensure non-experts have access to quality, personalized information [11].

Commercial channels are those from installers or the broader industry directly selling the technology, and includes advertisements, articles, and personal consultations. Personalized information is usually delivered through a quotation, where a representative will visit the building to assess the current situation, make simple calculations, and provide a short report that describes the expected performance of the system and the cost to acquire it. The level of trust in this information will depend on the provider's reputation (e.g. recommended by trusted peer or public ratings) and the comparison of this information with what is already known generally about the technology. One risk is that if they only receive one offer, which is common [12], [13], then the decision maker may not have enough background to evaluate the quality of the information they've been given.

One check against the trustworthiness of commercial information sources are peers. Peers are trusted non-experts within a social network that preferably have direct experience with a given technology. The influence of peers is well documented and can come at several points in the decision making process [14], [15]. The input of a trusted peer acts as a proxy for the decision maker who cannot "test" the technology for themselves. This applies not only for the technology, but also for the installer, much like many of the trades in the building industry.

The gathering of information through any or all these channels is an educational process that typically proceeds from more general information towards personalized solutions [10], [11]. This is represented in Fig. 1 by the arrows of progress, moving from initial interest, to gaining knowledge, to forming an opinion. Due to the high effort needed to create personalized designs and recommendations, this information typically comes from commercial channels since the costs are recouped through a sale. This creates a natural conflict of interest in that the party providing the education is doing so to sell the technology(ies) they are educating about. If a decision maker arrives at this stage of the process without sufficient general knowledge about how the technology should work and cost, then an information asymmetry forms between the buyer and seller.

Information asymmetry is a situation where one party in a transaction has more information about the product or service than the other. If the knowledgeable party uses this information to their advantage, it can lead to inefficient transactions which scale up to create inefficient markets, or in the worst case a market failure [16]. Failure occurs when trust in the market erodes and the quality of goods degrades [17], and inefficient transactions are those where the buyer does not get the product they want or should have [18]. For example, the seller of solar PV will earn more money selling a larger system, therefore they are incentivized to convince the buyer that the larger system is better and can use their superior knowledge about the technology and market to do so [13].

B. Motivation for DEAs

Energy technologies are particularly susceptible to the shortcomings of information asymmetry given their long lifetimes, meaning performance benchmarks may not be known until years later, if they are being followed at all [19]. The energy transition is already delayed, and if information asymmetry is left unchecked, the likelihood of a suboptimal societal outcome increases [20]. Digitalization (i.e. information and communication technologies, ICT) has enabled new methods for collecting, processing, and distributing information at scale, including energy systems. Combining well developed building energy systems models with modern data flows means it is possible to provide nearly every building owner with personalized energy consultations at the same level or better than current commercial or non-commercial sources. If made available as part of a public service, free from commercial bias, such a platform would act as an educational tool for decision makers, help reduce information asymmetry, and retain trust in the marketplace.

II. Methodology

Scientific articles and conference papers are used to describe the current state-of-the-art in large-scale building stock and urban simulations. This is complemented by a review of several openly published models and used to describe the general structure (or structures) and pathways towards the construction of an open building model platform.

This material is complemented by conversations with several relevant stakeholders within the field but from various perspectives. These are not formally structured interviews, but information gathering exercises of either an exploratory nature or as part of the direct collection of information for modeling, and consent has been provided by those whose direct insights have been documented here. The stakeholders are represented in Fig. 1, and include government energy advisors, private energy advisors, energy companies, and energy researchers working on UBEMs in both academia and industry.

III. What is a Digital Energy Advisor?

A digital energy advisor (DEA) would be an information resource comparable to a human energy advisor; they know what your current needs for energy are and can provide personalized recommendations on what energy renovations can be made to reach environmental and/or economic goals. In more technical terms, it is a piece of software intaking multiple forms of data, running energy simulations, and returning system designs guided by multiple objectives which can be prioritized by the user. Since pure optimization is rarely desired by the target user group, the DEA must have the ability to alter inputs or objectives towards the goal of educating the user about their alternatives and which factors impact them the most. The DEA's goal should be that the end user becomes educated about their options towards meeting sustainability goals in a technologically neutral way. This is distinct from existing commercial tools which are used as sales leads and non-commercial tools which lack personalization.

A. Why Should A DEA Be Built?

In addition to the problem of information asymmetry described in the introduction, conversations with energy advisors provide additional motivation on why a tool like this is useful.

Government energy advisors are available at no cost in all municipalities in Sweden. This public service is meant to reduce the barriers for building owners to identify methods for saving energy and money. The advisors say that existing tools are inadequate for their needs; commercial software is both costly and time consuming, and the tool developed by the Swedish Energy Agency for energy advisors is too detailed and complicated, also requiring too much time and effort to use. The typical consultation includes visiting the property, reviewing energy meter data, and making recommendations based on experience. Rarely are detailed calculations made. When the DEA concept and ongoing development were described, both advisors felt this would be a very useful tool that would bring quantitative analysis back into their consultations.

Their desire for a better tool comes in part from the stage of decision making many residents are in when they book a consultation. In 2022/23, most consultations (estimated at 70%) are to review solar PV possibilities. Of those cases, about 1/3 also ask about batteries. Many have already received offers from installers and are only looking to confirm that their offers are reasonable. This is certainly a suitable and appropriate use of the government energy advisors but does indicate a trend that efficiency is not at the front of mind for many building owners. In appropriate cases, the advisors say they try to encourage efficiency renovations prior to adding solar supply, but few consider it suggesting that they have already formed most of their opinion prior to the consultation. There are several reasons why efficiency and demand reduction has not been adopted as much as desired [21], [22], [23], including some that a DEA could not fix, but the ability to directly compare efficiency and supply alternatives with personalized simulations could make a positive contribution.

B. *What Has Already Been Built?*

Some forms of a DEA aimed at the direct education of building owners have been or are under construction. Many of these are solar energy related due to the relative ease of acquiring the data needed for the calculations. Perhaps the most prominent example is Google Sunroof [24], which provides energy production calculations and, in some markets, rudimentary economic calculations. The Sunroof database is also available to developers through an API and is embedded is several commercial sales tools, such as Solargraf [25] and Aurora [26].

Another example based on the same concept as Sunroof is the solar map launched by the city of Karlstad in 2021 [27]. Users can find their roof, select up to three surfaces for installation, and they are provided with a recommended solar PV system design. The first graphic presented to users for their design is shown in Fig. 2 (translated from Swedish into English), which was designed to highlight self-consumption calculated with new machine learning models [28], [29]. Further down, users can change system design or other boundary conditions to customize the design or stress test economic conditions. The primary aim of the tool is to educate, and was tested to identify language, metrics, and features that were most useful to end users [30]. This experience was a first step towards the development of a more comprehensive DEA.

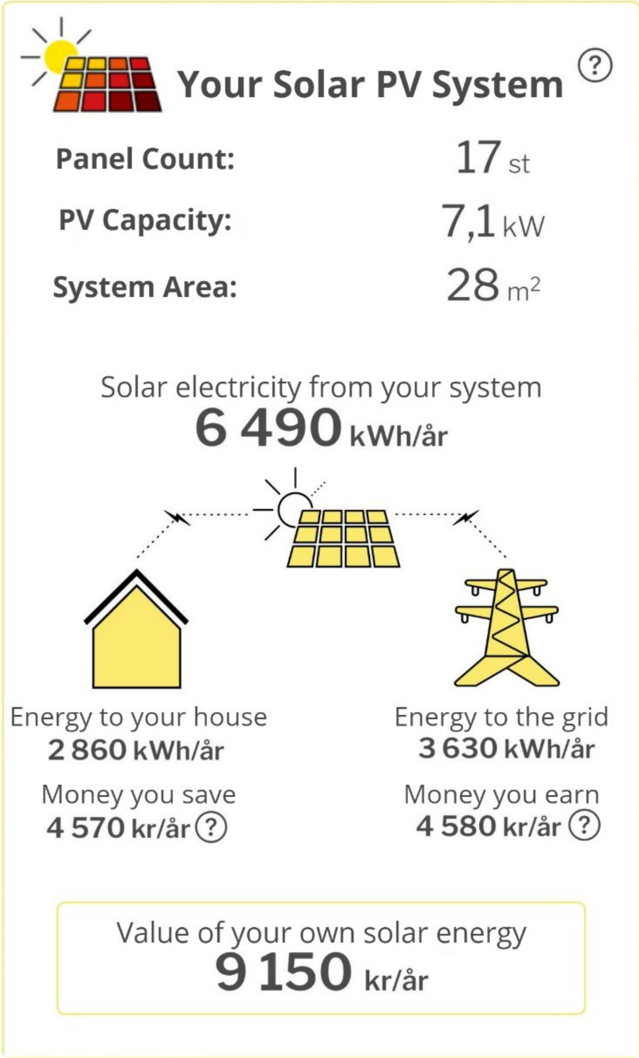

Fig. 2. Results page (translated to English) from Karlstads Solar Map [27]

Another tool that is closer to the DEA concept described above is made by the company Hemma [31]. Their tool is provided to consumer facing businesses (i.e. B2C) to attract customers and deliver energy renovations. One target customer are banks, where the tool helps collect information useful for a renovation loan. Another is installation firms which use it to help sell energy technologies. Hemma requires users to share their electricity meter data, which can be done digitally and automatically. Then they answer several questions about the building, which help feed into the building energy model, and the result is a list of energy renovation recommendations with their energy and cost savings. So in the model described in Fig. 1, Hemma is an energy advisor, but commercial rather than public. Their results currently do not allow users to adjust inputs or test alternatives beyond what they offer, leaving this instead for installers who can make a direct assessment. This is similar to nearly all of the commercial solar PV tools available as well [6].

IV. How can a DEA be built?

The ability to make academic/professional level calculations on a broad scale is becoming increasingly possible due to the development of building stock models (BSM) and their successor urban building energy models (UBEM). These models seek to create detailed, individual building energy models but at a district or city scale (e.g. from dozens to thousands of buildings). The core building models are comparable to single building models, and the added value of a UBEM is the ability to apply boundary conditions at scale. Generating this information automatically can reduce the barriers to high quality analysis and increases society's intelligence with regards to energy and sustainability. This chapter presents the basic structure of these tools, their data requirements, and the potential use cases.

A. Urban Building Energy Models

Building energy models have existed for decades and are used predominantly for single buildings. Methods for simulating large collections of buildings first started with building stock models, which are generally a large collection of architypes simulated independently and aggregated in a way that matches the building characteristics of a given region [32], [33]. UBEMs add a spatial component where specific buildings are mapped to specific locations in space. This can enable effects of shadowing on heating, cooling, and solar energy production, as well as urban heat island effects [34], [35]. But most relevant to this discussion is their ability to process large numbers of simulations and report that information in a spatially relevant manner.

The UBEM workflow is very similar to typical building energy models, as shown in Fig. 3, with special aspects that make it possible to apply properties at scale. It begins with urban geometry, namely buildings, but can also include trees and other objects that cause significant shading. Each building is then populated with characteristics like window areas and thermal properties, and internal gains consisting of occupancy and appliance usage. Due to the model's large scale, simulations are often made in stages to avoid rerunning aspects that are not always relevant. For example, a solar radiation simulation can be run to calculate incident irradiation on all surfaces once the geometry is set, and it does not need to be repeated unless geometry changes. Similarly, target energy usage such as thermal demand or solar supply potential, can all be run and visualized independently. Once demand profiles are generated, energy supply systems can be designed and simulated. At a more advanced level, district energy supply systems can also be designed and simulated.

A core difference between traditional building energy models and UBEMs is the need for systems and automation [36]. This is relevant for applying boundary conditions, validating models, and visualizing outputs, and creates new challenges in simulation. For example, if simulating 10,000 buildings, it is impossible to check the inputs of every single one to ensure they are correct. This places greater pressure on input data quality prior to model construction. It also makes simpler physics models more desirable, even at the sacrifice of accuracy, to reduce the number of failure points [37], [38], [39]. Likewise, the outputs of UBEMs become databases of their own, and create new opportunities for data visualization through digital twins or other GIS based tools [40], [41], [42].

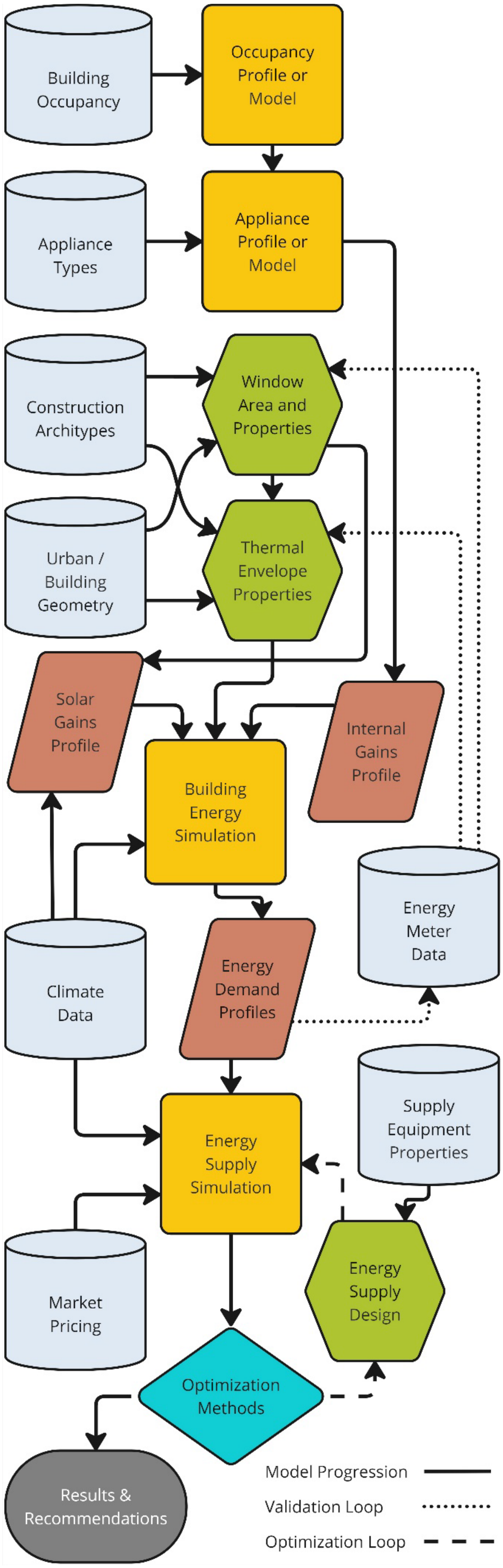

Fig. 3. Physics based building energy model structure and workflow

B. Data Requirements

Simulating an entire city requires a large volume of data from diverse sources. Following the workflow described in Fig. 3, there are eight data input points that can either be collected directly or derived from multiple sources.

Urban geometry can be generated using two main methods; 2.5D extrusions and 3D models. The extrusions come from 2D property maps which can be readily found in private and public domains, such as OpenStreetMap [43]. The maps contain building footprints which are extruded skywards to create the building volume. Procuring the correct height data can be a challenge, especially with buildings that have multiple heights in different parts. Full 3D data is usually constructed with LIDAR scans taken from low flying aircraft. This captures not only building geometry, but also vegetation, making this data type more valuable for solar shading. A substantial amount of post-processing is needed to convert a LIDAR point cloud into usable polygons, especially for buildings since they are simulated using one polygon per wall surface. There are two main formatting standards for 3D geometry, GeoJSON and CityGML, with the former becoming common in North American and the latter in Europe. There are already workflows established in some UBEMs built around both formats, and it is useful for each region to have a common format to converge upon [44], however there could be barriers to intercontinental collaboration. The effort needed to create a 3D dataset of high enough quality for use in UBEMs usually means only densely developed areas are generated and gaining access has a cost.

Building characteristics refer to the construction as it relates to thermal energy; e.g. U-value of envelope, window areas, infiltration rates, and thermal mass. When developing new construction, these values are known (within a level of uncertainty) since they are chosen in the design or measured during construction. In existing buildings, what can be known about the construction is highly variable. Gathering this data usually requires an energy audit, which is expensive and even then comes with high uncertainty about specific values. The EU project Tabula has helped create characterized residential buildings by age, including original and renovated values, which provides representative values for these classes of buildings [45]. A report from the Swedish National Board of Housing, Building and Planning (Boverket) presents a detailed audit of thousands of buildings subsequently turned into a validated building stock model [46]. In North America, the U.S. Department of Energy has generated a large, open dataset of detailed simulations for a variety of buildings in all climate zones [47]. In all cases, the boundary conditions used in these models should be considered typical of a given building class, i.e. architypes, providing a useful starting point for simulation, but still leaves variance in the deviations many buildings have from the norm.

The occupancy and activities within a building are used for four purposes; to apply internal heat and moisture gains that affect the HVAC system, to create electricity load profiles for equipment, to create hot and cold water use profiles, and to identify periods when humans are present and comfort requirements are needed in the HVAC controls. When building stocks or districts are the model target, generic profiles are commonly used since the nuances of individual homes are lost. But there are cases where capturing individual details are important, and several stochastic models are available which use total occupants as an input to create representative time-series profiles based on high resolution measurements [48]. Like the building characteristics, these profiles are only representative of a certain group of people and are usually limited to residential applications. Commercial buildings are too diverse to create such models easily and may instead require fixed profiles [49].

With the building models populated, the climate data is the final boundary condition in order to generate demand profiles. Weather data is often available from national weather services and a growing number of private sources, such as Meteonorm [50] and Solcast [51]. National weather data can be limited to specific ground stations, and is commonly unprocessed, meaning bad values need to be cleaned after the data is acquired. Private services use a combination of satellite and ground measurement data in proprietary models to create weather profiles for nearly any location on earth, free from bad values. A similar publicly funded tool, PVGIS [52], can offer the same but with only satellite data, and therefore comes with some additional uncertainty. Hourly timesteps have become the standard resolution for both weather data and simulations, however for electrical network studies including solar PV it may be necessary to use 15 or even one-minute timesteps [53]. For simulations meant to represent long-term behavior, a typical meteorological year (TMY) file is used so that only one year is simulated which can be extrapolated over decades. However, it is increasingly common to test weather under several climate change scenarios as part of the planning process. When validating, then temporally and spatially matched weather data is needed.

Validation is represented in Fig. 3 by a dotted feedback loop between the output demand profile and the building properties and requires energy meter data as a baseline comparison. In UBEMs, this process must be automated if a scale beyond a single district is required, which is possible through several methods [36], but is not trivial due to the need for numerous simulations and is not a feature in any UBEM tool. ASHRAE standard 140 is a common method that validates a model if the normalized mean bias error (NMBE) is maximum 5% and the root mean square error (RMSE) within 15% at a monthly timescale. If using an hourly timestep, NMBE and RMSE are increased to 10% and 30%, respectively, to account for greater stochasticity. At scale, acquiring energy meter data comes with several challenges, particularly when high spatial resolution (i.e. individual buildings) is desired. Another alternative is energy performance certificates (EPC), which are publicly available for individual buildings so long as the requester registers their personal data and interest, but access to the full database is only reserved for researchers. EPCs contain individual energy flows, but only with annual totals, and recent studies have demonstrated that at a district level EPCs can be validated against, but for individual buildings the errors become excessive [54], [55].

With validated demand profiles, energy supply systems can be designed and simulated. This requires technical properties for each component to be defined, such as conversion efficiencies or storage loss rates. These parameters can often be found through product specification sheets, but in some cases the full spectrum of technical aspects is kept private (e.g. heat pump performance maps) and regression models are used in their place [56], [57].

If an economic analysis is sought, then market prices for equipment and energy are needed. Current equipment prices are rarely published publicly, but are also highly variable, so industry statistics are suitable and usually combined with a sensitivity analysis. Electricity, fuel, and/or heating network prices are typically available via local utilities for free, but require manual collection and processing. This task can be substantial particularly when dealing with multiple local distribution system operators (DSO) that have differing price models. Manual collection of hourly electricity prices is also time consuming and automated access via an API can come with a cost; for example, Nord Pool Spot charges €3200 per year to commercial entities with a 50% discount for academic use. The OpenEI utility rate database in the United States aims to automate the process at a large geographical scale [58], including data for 3829 utilities, however updates are not generally fast enough to maintain pace with market changes.

C. Practical UBEM Tools

UBEMs are complex tools that require expertise, therefore the majority of UBEMs are built and used by two classes of professional: architects/engineers (AE) and researchers (i.e. any professional in a research capacity). The AE class uses UBEMs in the design of new city districts, for example to calculate daylighting or ensure compliance with energy regulations. Here the building geometry and characteristics are known (or are a result of the simulations) which means there is more control over the modeling process and in some sense simplifies the workflow. Simulating existing cities are largely performed by researchers towards the goal of greater understanding about the built environment or informing public policy.

The majority of UBEMs have been produced by researchers and tend to be open-source software. Two popular versions are the Ladybug suite of tools [59], [60], and City Energy Analyst (CEA) that comes from ETH Zurich [61]. The Ladybug tools are built using open-source models from the U.S. Department of Energy, such as the venerable EnergyPlus [62]. Their integration with 3D modeling tools popular with architects (e.g. Rhinoceros and Grasshopper) make them easily accessible by the AE class. CEA has Open Street Map integration for importing building footprints and urban infrastructure (e.g. roads) and therefore aims more at simulating existing cities. Like Ladybug, CEA is open-source and free to use, and the group supporting the tool was awarded funding in 2023 to boost support and further development.

There are many other UBEMs found in the literature, such as SimStadt [63], CitySim [64], and PyCity [65]. They are commonly born from a university or national lab research group and have variable levels of maturity or adoption. Sweden has two such tools developed within the past five years, one from KTH [66] and one from Uppsala University [67]. Both are wrappers which build a network of EnergyPlus models. Many are text-only, which further limits accessibility, and well-formed graphical interfaces are one reason why Ladybug and CEA have garnered larger user bases.

Another access point to UBEMs is through digital twins, a virtual representation of the city where sensor data is gathered to gain real-time insights and inform simulations. The simulation portion of an urban digital twin would be via UBEM. Largely a topic of research, digital twins have mostly been constrained to single buildings, or at least single owners of a building portfolio (including public entities), due to data access. An energy utility, such as the DSO or district heating operator, would be well positioned to generate an urban digital twin using energy meter data, however much like the raw meter data, this representation would be restricted to internal use only to protect privacy.

V. Barriers to Building a DEA

The design and renovation of energy utilization in buildings and cities is supported by computer simulation tools developed by researchers and utilized by commercial firms to inform individual customers. With the simulation framework provided by UBEMs and the large volumes of data now being systematically collected throughout society, it is technically possible to generate information with the detail of a commercial firm at the scale previously reserved for generic rules-of-thumb. However, access to all the datasets listed in Fig. 3 for the purpose of building a DEA is challenging, in particular high-resolution urban geometry and model validation data.

A. Building and Urban Geometry

Building geometry is categorized with a level of detail (LoD) system from ranging from 0 to 3, and includes subcategories at each level as shown in Fig. 4. Most building stock models and UBEMs are simulated using LoD 1.x geometry, or essentially boxes, which are generated using the 2.5D extrusion method. For thermal-only simulations, LoD 1.3 is the acceptable minimum resolution and commonly applied in building stock or UBEM models. However, solar energy potential requires greater detail in the roof, for pre-feasibility 2.2 is acceptable, but for final design, LoD 3.2 is necessary as it captures smaller roof objects like ventilation pipes, chimneys, or ladders, and not only roof geometry [68]. The state-of-the-art tools use a combination of LIDAR and visual datasets, combined with machine learning image recognition, to identify smaller objects [69], [70].

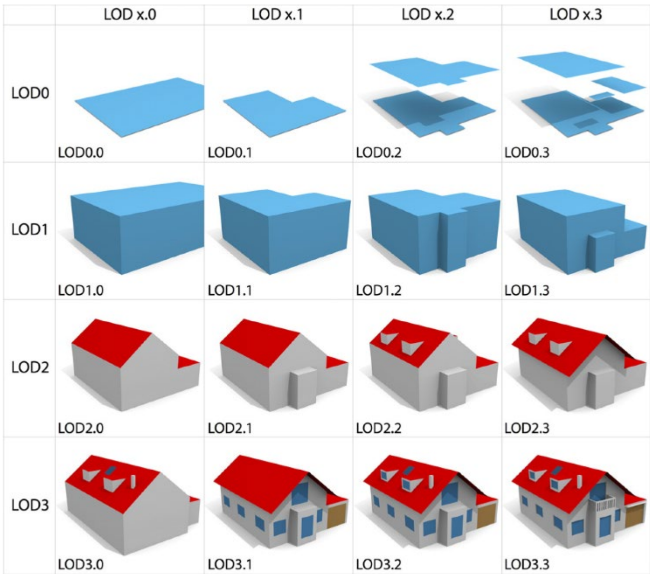

Fig. 4. Building model Level of Detail (LoD) classifications [71]

Access to geometry for building an energy model varies by scale and location. At a Swedish and European scale, building footprints (LoD 0.1) are readily available. Extruding these footprints into volumes requires data from other sources since building heights are not always included in the footprint data. In Sweden, the National Land Survey has building height data within GIS shapefiles, and the EPC database includes number of floors, which can be used to reach LoD 1.2.

However, this misses buildings where different portions have differing heights, making it impossible to automate geometry creation at LoD 1.3 without manual review. For districts this is time-consuming but manageable; at city or national scales it is not practically possible. When considering the energy demands for an entire district (e.g. for district energy supply), LoD 1.0 can be sufficient, however when targeting individual buildings for use in a DEA, then the errors generated by the incorrect heights become too great [54], [55].

A key point with any building geometry is that while data may be publicly available, it comes with a cost. Researchers working in a non-profit capacity have access to Swedish Land Survey data, but it is a municipality-by-municipality basis on whether 3D CityGML data is available at no cost or not. These datasets are mostly used by real estate developers which municipalities charge for, so it is likely that building a publicly open UBEM with this data would also come with a cost. One way to avoid this cost is for the municipalities to own or operate the DEA themselves, which is a model followed by many of the solar maps developed over the past decade. This approach helps to overcome the access to quality geometry barrier but requires that a UBEM is easy to implement within a municipality's existing data infrastructure.

Another geometry set that can be difficult or impossible to acquire is energy infrastructure. In the design of new or additional energy networks, the placement of current infrastructure becomes critical. Stockholm Exergi, the district heating network owner and operator in Stockholm, cannot share the location of the underground heating pipes throughout the city, making high spatial resolution studies about the economic feasibility of distributed heat sources nearly impossible. It is possible that not all cities have this restriction, as a capital city Stockholm may be unique, however the criticality of electricity and heating infrastructure to society and the threat of terrorist attacks suggests that keeping this information private may be a higher priority than a digital energy advisor.

B. *Energy Performance Certificates*

Energy performance certificates (EPC) are energy audit reports mandated by the EU. All public and commercial buildings must have them performed once per decade, and single-family homes must do them when changing ownership. They contain the most detailed set of information about a particular building at scale, including aspects about the building geometry, installed energy supply equipment, and metered energy consumption data. This information is useful for establishing boundary conditions as well as model validation, even if this was not their original intent [72]. The main limitation with EPCs is that the annual values fall short of commonly accepted validation methods which require at a minimum monthly values.

The Swedish National Board of Housing, Building and Planning (Boverket) is responsible for the dataset and sells limited access to the real estate industry through an API. The only energy data available in the API is primary energy per square meter (kWh/m^2) which obfuscates the ways in which energy is used in the building and insufficient for UBEM usage. However, the full dataset is available, free of charge, to non-profit researchers under the condition that none of the raw, original data is shared; only new insights generated from the research can be published. This condition is not a limitation for the construction of a UBEM. However, it does limit the transparency in that a user would not be able to know the boundary conditions used to create the model if they came directly from the EPC. This may also be a uniquely Swedish case since the city government in Helsinki, Finland publishes an energy map with EPC details [73], [74].

In addition to the low temporal resolution of the energy data, EPCs can also be unreliable in representing the current state of a building. The original aim of the EU directive for creating EPCs was to encourage energy efficient renovations, which could certainly be enacted within the 10-year gap between EPCs. Given that building renovations occur at a low 1-2% rate within the Swedish building stock [75], the risk for error is low, but for any given user/building the error could be dramatic. EPCs are also not available for every single building, meaning that educated assumptions would be needed to fill in gaps, either through statistical techniques or broader categorization taken from other sources like Tabula. In either case, the potential for error increases, and ideally higher spatiotemporal resolution energy usage data would be available for validation.

C. *Energy Meters*

Energy meters are possibly the most valuable data source for generating energy retrofit recommendations to decision makers. Electricity and gas meter data in its raw form can be and often is the basis for designing energy supply systems. But more crucially for UBEMs is the opportunity to validate the building energy demand model and improve boundary condition assumptions. Without matching a specific set of meter data to a specific building, validation becomes weaker. When combined with EPC data and/or other data processing techniques, it is possible to extract the energy usage of specific devices (e.g. heat pumps) and improve internal gain inputs to the UBEM. Even better is if the building uses district heating, in which heat and electricity demand data would already be separated with high temporal resolution. In Sweden most electricity meters have a one-hour time resolution, with the rollout of 15-minute resolution already under way.

Energy usage data is generated by end users and collected and stored by energy utilities, making researchers an outside third party. With the introduction of the general data protection regulation (GDPR) in Europe, a considerable barrier was placed against third parties gaining access to this data. The energy utilities are allowed to share the data without permission, but it must be anonymized and unlabeled such that no specific piece of data can be traced back to the one who generated it. The challenge is in a UBEM, where every single building can be simulated, the occupant(s) of that building can be identified and therefore must give their explicit permission for their meter data to be used for the purpose of simulation.

For researchers, individual permissions are a high barrier to overcome. The company Hemma collects permissions by using the BankID digital signature service, and then automatically connects to the user's smart meter. It should be technically possible for researchers to do the same, however most research projects are funded through individual project grants lasting 2-3 years and therefore practically challenging to establish the infrastructure to collect permissions and data for such a short duration. It is more practical and encouraged for researchers to work with energy companies, meaning that the researcher must have a trusted working relationship with the relevant company(s).

There are still many legal and ICT requirements for using industry data and complying with GDPR, which if not planned for in the project's administration can lead to long delays. A shift from physics based to data-driven models means energy researchers have seen an increase in time spent on data procurement and processing in recent years [76]. Any project aiming to use energy meter data must budget administrative time for multiple contracts and legal review, and the more standardized a department or university can be in these cases, the lower the burden is on researchers.

It is also possible that as the amount of data grows, along with the value of extracting insights of that data, the willingness for companies to share it for public publication or the public good could decline in favor of maintaining the value for themselves. With this or in cases where data must be kept private, research must then be conducted within the company, ensuring that the intellectual property remains under their control. A prominent parallel here are social media and internet gaming companies, which have been criticized in popular media for designing damaging features into their products [77], but are difficult to study by researchers outside the company [78].

VI. Discussion and Pathways Forward

The energy transition is under way, but most experts agree it is not happening fast enough to meet the most ambitious climate goals, or even the mediocre goals [79]. There are many who wish to take action, but do not always realize that the greatest impact they can make with a single decision is related to energy use in buildings due to both the scale of impact and durability of the decision. Other high-impact actions like diet and travel, require changes in habits, i.e. multiple decisions over time. This report works under the premise that an informed populous with access to true and transparent information is critical to maintain the acceleration of energy sustainability in buildings and cities. Information asymmetry is known to harm or even collapse markets [16], [17], and the time pressure on climate action does not allow for further setbacks.

In 2023, information about building energy retrofits in Sweden is dominated by the popularity of solar PV, which for the past decade has had a steady growth in annual installations rate of about 50% per year [80]. This demand was further pushed by the European energy crisis starting in 2022 when energy supply was in doubt and prices skyrocketed. Installers used the opportunity to highlight how much savings could come with PVs, sometimes using exaggerated assumptions [6] or selling larger systems than they may have otherwise [30]. While certainly a special situation, it highlights how low-quality information in the marketplace can lead to sub-optimal outcomes for those acquiring it. Even those who consult a neutral party, like the energy advisors consulted for this project, were often looking for confirmation that they were making a good decision, rather than a critical review.

The solar trend is frequently coupled with electric vehicles and stationary batteries; the former is indeed highly impactful towards environmental goals given the low emissions of Nordic electricity. The net benefits of stationary batteries are less clear [81], however there is a rapid development in building participation in ancillary markets due to strong economic incentives [82]. It has become less and less likely that building owners look to thermal efficiency, which is arguably more challenging than updating energy supply equipment [21], [22], [23]; replacing an older heat pump with a new, more efficient model is much easier than adding insulation or replacing windows. But given how much importance has been placed on the energy efficiency of society in meeting environmental goals [2], the prioritization of prosumer technologies over efficiency presents a challenge.

Urban building energy models, which include demand and supply, have the potential of providing every building owner with detailed information and holistic recommendations about how they can invest in their property towards their technical, economic, and environmental goals. The rise and popularity of solar maps demonstrates the impact this approach can have, however there needs to be a version curated by non-commercial stakeholders to avoid the continued generation of misinformation for the purpose of sales [6]. To be certain, rooftop solar is a good thing, but if the limited investment potential of the building owner is used to buy solar when it could have been used more effectively to solve sustainability challenges on another efficiency measure, then this is a lost opportunity that slows the energy transition's progress.

The ability for non-commercial actors to generate such an information source is hindered by several barriers to data, through the data not being in existence, or more prescient is the inability to gain access to critical validation data due to a need to protect privacy. Commercial actors in the digital property technology (i.e. "prop tech") space are beginning to realize the potential of such a tool and several examples have been covered here. Time will tell if these tools can provide sober, neutral advice about the range of renovation options available, or if the need to finance them through sales referrals will nudge results in a positive direction for one or several particular technologies. This not to say that commercial actors are not capable of providing the information decisions makers seek. But the message of non-commercial actors, which are already considered a valuable counterweight against information asymmetry, could be given greater reach with a transparent urban energy model deployed at a national level. Such a tool would be an asset for municipal energy advisors, or anyone looking to help another make an informed decision.

The laws surrounding ownership and protection of personal data are not being challenged here. Data protection and ownership laws in the EU are particularly well positioned to give more rights to individuals as compared to other large economies. It is simply documented here that these laws create barriers to generating new and useful information that those same individuals could benefit from. But there are potential pathways around these barriers towards successful creation of a digital energy advisor.

The barriers to building geometry are centered around cost and access. High resolution 3D mapping towards levels of detail suitable for rooftop solar planning require expensive input data and substantial post processing. Giving this information away for free is not possible without public support. Since many municipalities are already funding the generation of these datasets, it can be the case that they are also the natural host for a future DEA. This model follows the already established solar maps, and the investment can be motivated by the need for new tools to support municipal energy advisors. There remain issues around coverage, as buildings which are not located close to dense urban areas are unlikely to have a high LoD. Here improvements in machine learning techniques with aerial photography have great potential. While still not free from cost, they can use existing datasets and avoid expensive LIDAR data capture. There is ongoing work in this space, both in research [69], [70] and in the private sector, most notable by Google who released an updated version of their Sunroof product in late 2023 that leverages image recognition techniques [24].

Developing work-arounds for energy meter data can be found in data driven models. One alternative is a clustering analysis, which could map energy signatures to specific parameters on the public EPC. A major limitation of this approach is the aforementioned coverage that EPCs have amongst buildings, and the possibility that renovations could have occurred following the most recent EPC. It also continues reliance on access to the original dataset, which will not be available after the completion of a project. Here a black-box model could be developed to create representative energy demand profiles. Since the outputs from the model are not exact meter data, they are not violating privacy laws. The validity of such a model will not be as strong as one where specific meter data can be mapped to specific buildings. However, if the target building is not an outlier, it is likely that a suitably representative demand profile can be generated. Work on this pathway is ongoing with results expected in late 2024 [8].

In addition to technical aspects, more work is needed to understand how end users would utilize such a tool, to help frame and present information in the best possible way that is not strictly seeking to make sale. A notable limitation for non-expert users is their inability to understand which inputs they may wish to change and how to learn from the tool [30], [83]. Therefore, design for guided use with human energy advisors should be considered in the short term, and fully automated guided use in the longer term. Generative AI tools like ChatGPT, once trained how to extract useful insights, would then become a fully digital energy advisor. Since the underlying physical models are based on UBEMs, with hundreds or thousands of building models, it would also be possible to build a DEA for professional energy planners, extracting novel insights for district, city, or national scales. All of this relies on the ability to circumvent data barriers and build useful and validated models.

Given the potential demand for a DEA and the number of corporate interests participating in the field, it could be that an open-source business model is the ideal pathway to overcome the barriers described throughout the paper. A commercial entity would be able to handle infrastructure and legal matters regarding data and would be in a strategic partnership with researchers to develop and validate new models. This is the approach used by Hugging Face [84] and caused an acceleration in the development of natural language processing models. The scale and scope of a DEA could greatly benefit from the same acceleration.

VII. Conclusion

In this paper, we have explored what would be required to implement a Digital Energy Advisor (DEA), which would be capable of automatically guiding building owners towards sustainable renovations. We conclude that a DEA would be utilized by municipalities and that such a tool in principle could be possible soon with dedicated development efforts. Moreover, a DEA could have great potential to support households with unbiased advice on energy investments, and that this could be highly relevant from a societal perspective.

We also conclude that existing tools are insufficient in producing the high-spatial and temporal analysis required of a DEA due to a number of obstacles to the implementation, mainly in terms of data. The obstacles are more related towards the accessibility of data than about availability of data, which act as a barrier to model creation and validation.

The main obstacles in terms of data availability can be referred to either legal or commercial interests. The former are related to safeguarding individuals' integrity and corporate intellectual property; the latter relates to the competition for researchers to access private company data or cases where data kept for self-serving future opportunities. While both those reasons may be understandable and justifiable, the benefits of a DEA are great enough that further investigations are needed to identify how the data and models to create a DEA can be made available without jeopardizing integrity. An open-source business model that encourages private-public partnership in the creation and execution of a DEA is the recommended pathway forward.

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