Machine learning for green smart homes

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Abstract. Smarter approaches to data processing are essential to realise the potential benefits of the exponential growth in energy data in homes from a variety of sources, such as smart meters, sensors and other devices. Machine Learning encompasses several techniques to process and visualise data. Each technique is specifically suited to certain data types and problems, whether it be supervised, unsupervised or reinforcement learning. These techniques can be applied to increase the efficient use of energy within a home, enable better and more accurate home owner decision making and help contribute to greener building stock. This chapter presents the state-of-the-art in this area and looks forward to potential new uses for machine learning in renewable energy data.

Keywords: Machine learning, Smart home, Energy management, Energy modelling, Green buildings, Big data

1 Introduction

In the past, humankind had no other choice than to build sustainable habitations. Whatever they made was out of natural and local materials. People were forced to plan accordingly to survive from the resources available. With time, human groups started to gather together in small tribes, villages and farms, and then bigger and bigger cities. By the 1970s, it was obvious that the ever-growing demand for power and materials, inefficient power systems, poorly planned buildings, and the demand for more comfortable homes with heating and cooling systems, would not be sustainable and climate change became a real concern.

Over the years, the idea of smart green (sustainable) cities has developed. An United Nations Economic Commission for Europe (UNECE) and International Telecommunication Union (ITU) [70] joint initiative (with a consortium of over 300 international experts) coined the concept of smart sustainable cities as *a city that explores Information and Communication Technology (ICT) and other available resources to improve efficiency of urban operations and/or services, enhance competitiveness to improve its citizens quality of life*. Such a city targets the social, economic, cultural and environmental needs of the present and for generations to come. This concept is well structured and documented with its own Key Performance Indicators (KPIs) [21].

Additionally, with energy prices rising (e.g., fossil fuels and natural gas), the pressure for energy consumption reduction is a reality. The concept of the green (or *eco*) home addresses both concerns: climate change and energy consumption reduction. Green smart homes are an integral part of the smart green cities concept, and a very important tool to address several of its core objectives.

The energy sector alone is responsible for roughly 75% of all Greenhouse Gas (GHG) emissions. Residential energy consumption represents 20% of the overall energy sector, as depicted in Figure 1.

Buildings alone are one of the biggest emitters of GHGs [67], with domestic buildings responsible for approximately 21% of energy consumption and 21% of GHG emissions [5]. It is vital that we address this to help meet the challenges of the Sustainable Development Goals (SDG), EU Climate Targets and the various Climate Actions Plans throughout the world [69].

Despite the efforts to tackle climate change, CO_2 emissions (from industry and energy sectors) have increased nearly 60% - since the United Nations Framework Convention on Climate Change (UNFCCC) [71] in 1992, parent treaty of the 2015 Paris Agreement [68].

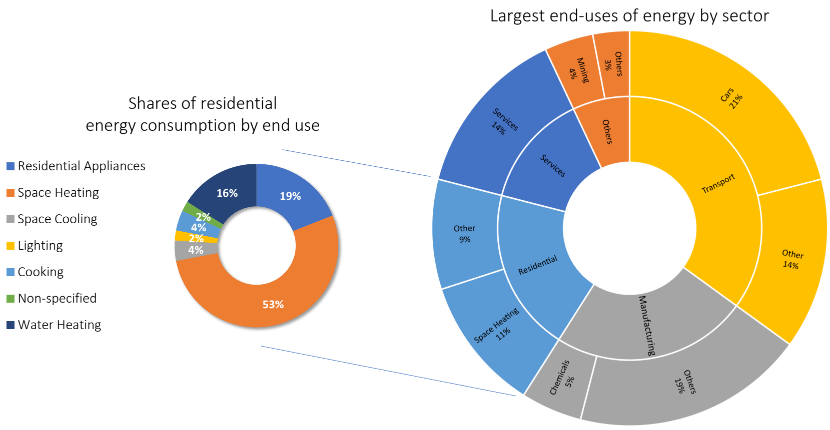

Fig. 1. Energy Efficiency Indicators – IEA 2018/2020 [31]

The IEA report "Net Zero by 2050" [32] establishes a roadmap of around 400 milestones with necessary global actions and commitments detailing when and what to do to decarbonise the economy in the next three decades to limit the average global temperature increase to 1.5°C.

Such audacious goals demand a complete revolution on how we produce, transport and consume energy. This chapter explores how machine learning can help improve the performance of green smart homes and contribute to the creation of a cleaner and more resilient energy system. To contextualise the smart home concept evolution, let's dig a little back in time and explore the technology history from the early twentieth century up to today.

1.1 A little history

It all started in the first two decades of the twentieth century with appliances that would not be considered smart as we understand them today, but were nevertheless revolutionary. The first models of vacuum cleaners (engine-powered in 1901 and an electricity-powered model six years later, in 1907), refrigerators, dishwashers, washing machines, and toasters were just the beginning [11].

From the 1960s, electronics became more popular and accessible with the touch screens [36], computer-aided home operators [49, 63], and the ARPAnet project [13] with Tim Bernes-Lee [72] paving the way for the Internet. The following decades witnessed many more innovations with environmentally friendly washers and dryers in the 1990s, and later robotic vacuum cleaner prototypes.

One of the first examples, of what would become "smart tech", comes from "Gerontechnology" (early 90's) [28], with special devices (trip/fall buttons) to improve senior citizens' lives. In parallel, mobile data exchange on 2G networks in Finland was followed by the standardised IEEE 802.11 Wi-Fi model [33].

The convergence of groups of technologies in hardware (more reliable and smaller devices), the Internet, and wireless communication made it possible to create the smart homes we know today. Well known examples of these technologies are Amazon®'s Echo and Alexa, Google®Home, and Apple®'s Siri voice activated devices and also Google®Nest (Learning) thermostat.

1.2 Where are we today?

Roughly 75% of buildings in Europe are energy inefficient and most of them (85% - 95%) will still be around by 2050 [23, 24], see Figure 2. Building floor areas globally are estimated to double by 2060. As urbanisation in emerging markets increases, the demand for housing in urban areas increases and concentrates growth in residential construction [59] – with an average of 25% of non-residential against 75% of residential units.

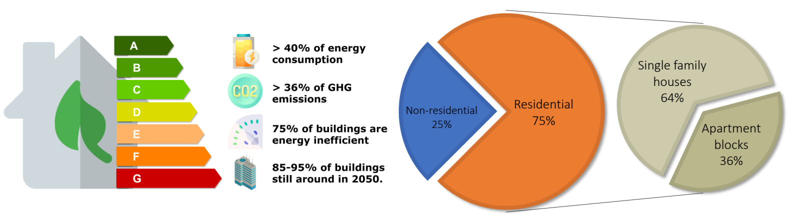

Fig. 2. EU Building Stock [23, 24]

These scenarios pose very challenging goals as the building stock energy consumption is responsible for roughly 36% of GHG emissions. Green smart homes can offer significant improvements for the building stock energy performance to address these challenges. By implementing intelligent ways to manage and control the homes' energy consumption, green smart homes can provide ways to minimise energy consumption/carbon emission and, by doing so, reduce the overall home energy costs and raise the property value. This enhanced management is dependent on the capacity of the green smart home to collect data from its environment (e.g., temperature, luminosity, and occupancy) and consumption behaviours (e.g., smart meters and appliances usage), and to interact with smart appliances and other devices.

Processing the data collected can be a challenge in itself. As smart home systems evolve and integrate, big data issues (explored in Section 4) become more obvious. The four V's of big data are usually present:

- Volume: the more data a system can collect, the more accurate its measurements and model predictions will be;
- Variety: data come from diverse types of hardware and protocols, making data integration harder;
- Velocity: the velocity of data collection depends on the time resolution and the number of sensors and devices monitored. It can present a real challenge to integrate and synchronise the monitored units into a single platform;
- Veracity: is concerned with the data quality, reliability, and availability.

Finally, artificial intelligence and machine learning can help leverage value from the data by properly exploring the home energy data and adapting the energy consumption dynamically to new conditions and demands [59] using data-oriented decision-making for better planning, management, and policy-making.

2 Smart Green Homes

The term "smart" has become a generic term over the years. Frequently used frivolously as an adjective to qualify some new or innovative product or service (not necessarily attached to the use of machine learning or artificial intelligence, but at least having some level of computer-aided control) [29], the term has become a very popular marketing tool. However, in our scope, the term "smart" is a technology capable of collecting information about its surroundings and offering some level of intelligent reaction to the scenario described by the data - in combination (or not) with other data sources [44].

What once was limited to control "environmental" systems in a home (e.g., heating) has evolved to encompass almost every electrical device in use in a house [57], from rooftops (photovoltaic panels and solar water heating), bedrooms and commons areas (heating and cooling systems, doors and windows sensors, smart lighting and thermostat), kitchen (energy-efficient appliances operation), smart meters (fro electricity and gas consumption) and smart meters to manage all resources consumption (e.g., electricity, gas, water) [59]. As the devices become "*smarter and smarter*", they become capable of communicating with each other and operating based on predefined behaviour.

As these devices (e.g., sensors, controls and appliances) are getting interconnected in networks, smart homes grow in complexity, interoperability and data collection become easily available. The "green" smart homes come from the potential that smart homes have to address the reduction of energy consumption and emission of associated GHG - and help in the green energy transition.

Also, the volume of data grows exponentially and big data (refer to section 4) connected to smart homes becomes a necessity. One example that justifies the urge in dealing with such data volumes of data is illustrated in Figure 3. The amount of time between data collection and the proper action has a direct impact on the energy savings of a household.

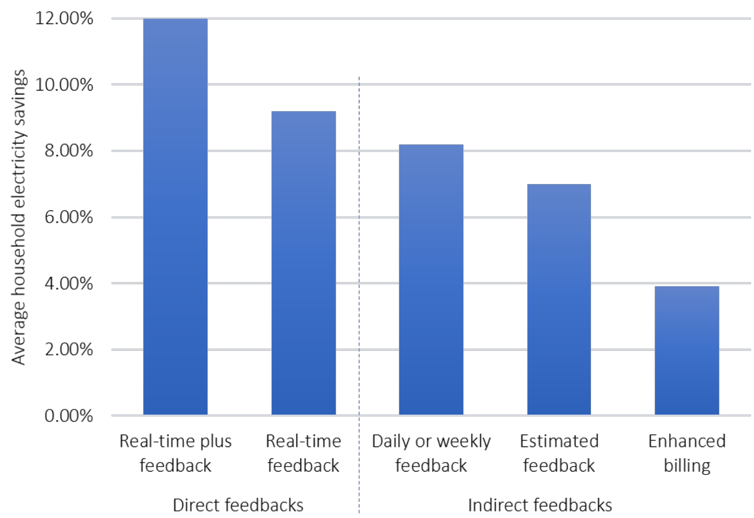

Fig. 3. Average household electricity savings by feedback type [42]

Moreover, machine learning applied to residential data becomes viable (refer to section 5) and, in conjunction with energy modelling techniques and home energy management (refer to sections 6 and 3), green smart homes now can grow into a valuable tool to significantly impact the carbon footprint reduction.

Therefore, most of the potential for energy saving comes from monitoring (usage and behaviour) and developing proper automation to make the most of the energy available. Occupancy-based lighting and smart thermostats, optimisation and/or recommendations on better energy consumption profiles are only a few examples of what can be achieved. Data-driven decisions, in both local (operational) level and in policy-making (planning and investments) level, will lead to an improved building stock energy consumption.

In summary, green smart homes are a group of network-connected devices and applications capable of integrating sensors, appliances and an ever-growing list of other devices to allow remote monitoring, user comfort convenience and energy consumption performance improvement of households in the green energy transition.

3 Home Energy Management

A Home Energy Management System (HEMS) provide us with the means to integrate, monitor, automate and control the household's smart appliances and also renewable energy related devices (e.g., batteries, Photovoltaic (PV) panels and so on). Additionally, the HEMS can also encompass a broader integration including smart sensors, a whole heterogeneous universe of Internet of Things (IoT) devices, security, external partners and the power grid [39].

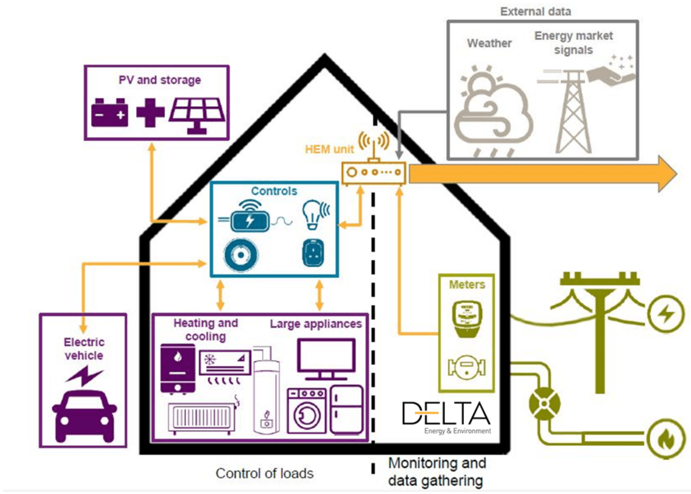

Fig. 4. Delta Home Energy Management (HEM) [37]

By doing so, the HEMS addresses the energy performance issue on households and also make it possible to explore eventual surplus energy generation that can be available (e.g., PV panels, wind power and/or battery energy storage) from and to interconnected partners in a distributed energy generation scheme. Typical examples of household appliances include, but are not limited to washing machines, dishwashers, electric vehicles (charging stations), dryer machines, air conditioning, water heaters, lamps, televisions and even battery/energy storage systems where local generation is present.

However, not all appliances and devices in a household allow the same level of interaction and control (if any at all), which can limit scheduling objectives due to physical and/or operational constraints. Table 1 shows a list of possible response classes of devices, as follows:

Response class	Description
Uncontrollable loads	Those are loads that should not or could not be under HEMS control usually because they can present operational limitations (e.g., a freezer or the essential lighting) or physical limitations (e.g., uncontrollable power generation from PV and/or wind).
Curtailable loads	This is the energy consumption load that can be curtailed without any later consequences and is usually made due to electricity price (e.g., lighting dimmed due to electricity price).
Uninterruptible loads	The load is necessary to complete a set of operations before finishing the task and can be modelled to consume a specific amount of energy (e.g., cloth washers and cloth dryers).
Interruptible loads	The loads must keep the devices or appliances close to a defined state (e.g., air conditioning and energy storage).
Energy storage	The loads are used to control how energy is stored or dispensed, and it is usually defined by load regulation restrictions.

Table 1. Response classes list [3]

Additionally, HEMSs must manage and coordinate loads in a scheduled manner. To achieve that - beyond the obvious communication and interconnection challenges - the HEMS has to deal with difficult integration issues. The lack of standardisation amongst diverse manufacturers in what concerns the devices and appliances communication/integration in a household (given that HEMS is a relatively new concept) poses significant barriers for the development and deployment of HEMSs.

For example, if a homeowner adds a new device to the house, the HEMS most likely will have difficulties to dynamically identifying and incorporating the new device. If it is a new Electric Vehicles (EV) in the garage, a new battery for renewable energy storage or an additional heater, the modelling and control of a myriad of distinct devices will demand reasonable flexibility from HEMSs. However, as home automation technologies advance and become more accessible/affordable, the research institutes and the market focus their efforts on the development of standardised ways for integration [61, 34] and the strengthening of HEMSs as a whole.

The goal is to promote a coordinated operation of these components and to create some level of integration between HEMSs. Even though its operation is usually on a demand-side (e.g., local energy savings), HEMS must interact somehow with the energy grid for proper supply in a dynamic energy load scheme. For that, a HEMS is usually composed of these components:

Smart appliances: household devices (e.g., heaters and air conditioning) and/or energy generators (e.g., PV and wind turbines), both improved with communication and (at least basic) computing functionalities, allow data exchange and interaction for operation coordination.

Sensing and measuring: sensing (e.g., temperature and motion detection) and measuring (e.g., smart meters for collecting data about energy consumption in general or about specific appliances and devices) [39].

User interaction: as HEMS is a user-centric technology from design, it demands a way to allow users/residents to interact with the HEMS functionalities. For that reason, it is expected user access, via some sort of interface (e.g., web interfaces or touch-screen devices), to check energy consumption, define operation preferences, comfort parameters and so on.

Centralised services: help the user to manage and use HEMS functionalities (especially in what concerns remote access), integrate the households (sharing data) and coordinate renewable energy exchange (or trading) [60].

The integrated operation of HEMSs seeks to provide the necessary data to the grid (so it can guarantee the energy supply), avoid (as much as possible) unnecessary demand stress and eventual outages. This coordinates operation can be developed in a centralised or in a distributed approach.

Each approach has its positive and negative points. The centralised approach concentrates all operations in a single processing point (usually giving access to all sorts of data, including private information) and demands heavy computational power to deal with the necessary analysis. However, as all necessary data is present, the results are expected to be more effective. Differently, the distributed approach expects the collaboration of distinct and independent components that will work together to develop demand-side plans and grid operation. Usually, the distributed approach does not share private data but, at the same time, it can have its performance negatively affected because it works with "*incomplete*" information.

Nevertheless, the integration of the HEMSs into to grid infrastructure is essential to achieve higher levels of grid stability and reliability – and it is especially important in Distributed Renewable Energy (DRE) generation schemes where each HEMS can be a potential renewable energy generator with "*erratic*" outputs.

In summary, HEMSs allows householders to manage and monitor appliances and devices energy consumption (in real-time or near real-time) in a planned operation manner. It can be understood as an evolution of the traditional smart features into a more effective role in what concerns power grid interconnected operations.

4 Big Data

Globally, data is increasing at an exponential rate and energy data is no different. As a result of the significant growth in ICT in buildings such as sensors and meters, data in buildings has the potential to change the way we monitor and manage building stock. Unfortunately, the data gathered is often not stored in a manner to maximise the opportunity for potential benefits from the data and this is a huge cause for concern given the rise in dark data [52].

The importance of finding good data is paramount to the success of research, and to meet the ambitious European Union 80% reduction goal in primary energy consumption by 2050 [22]. In support of the transition to an environmentally sustainable society, a significant amount of good or useful relevant data, is required that is capable of informing decisions on channelling future energy research, investment opportunities, in-depth policy analysis and delivering better national policies. Providing this data will be a considerable undertaking, requiring careful analysis of the V-based characterisations to achieve this.

V-based Characteristics: Big data uses a variety of "V" values when describing the V-based characteristics, for example IBM coined the 4Vs of Big Data for qualifying and quantifying the important factors, but up to 14Vs have been identified by others [54]. In the following list we have captured the 14Vs in no particular order, in order to ensure that all are considered:

- **Volume**: A we are dealing with big data, volume refers to the quantity of data.
- **Variety**: Due to the growing amount of data that is generated that is either structured or unstructured, variety refers to this.
- **Velocity**: The speed at which big data is generated, created, produced, or refreshed
- **Veracity**: Unfortunately, due to the volume of the data that is generated, created, produced or refreshed, confidence in such data is reduced.
- **Validity**: It is obviously important that the data we are using is valid, i.e. real data from a reliable source, using invalid data can skew results and lead to poor models.
- **Value**: The primary reason for data collection and processing is to extract value from it, without value then it would be a pointless exercise.
- **Variability**: If data was always the same then there would be no need to repeatedly gather it, data that is gathered typically changes over time.
- **Venue**: Where the actual data science work takes place, also where the data came from and where it was stored.
- **Vocabulary**: Refers to data terminology, including models and structures.
- **Vagueness**: Confusion over the data that was gathered and difficulty extracting meaning from it.
- **Visualisation**: With all data it is a struggle to visualise it in a meaningful way.
- **Virality**: Refers to how fast data is shared from source to another.
- **Volatility**: How long the data stored is of actual use to a user.
- **Viscosity**: The time lag between an event and when information was shared.

At present, the level of effort required in producing good data is placing huge demands on the producers and users of data, with a talent gap and skills shortage adding to the increasing list of the challenges that we are facing. In the short term, it is of critical importance that we address the rapidly increasing amount of data being generated from buildings, and to devise effective and reliable tools and methods that can be promptly put in place for its evaluation and use to secure a low carbon economy.

This problem can be addressed by applying a variety of methods, such as for example data classification, data optimisation, data mapping and standardisation. To meet the skills gap, we need to develop a knowledge sharing structure, a network of interconnected research centres, organisations and individuals helping one another to clean their data and maximise its usage for the global benefit. The availability of a database of building-related data providing relevant information quickly will have substantial benefits in both the building sector and a variety of sectors that contribute to the increasing greenhouse gas emissions.

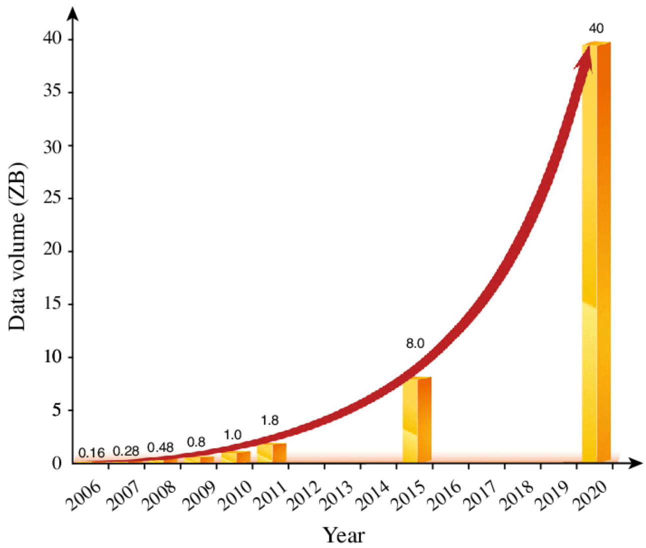

Fig. 5. Big Data Growth 2006-2020 [40]

It is extremely difficult to obtain high-quality data quickly or easily and obtaining buildings data is no exception. Data produce knowledge and as Sir Francis Bacon is quoted as saying *"Knowledge itself is power"*. It must be noted that whilst having good knowledge of our buildings does not necessarily mean good decisions, it does provide the means to make more informed decisions. At present, with all data, we struggle to get it right and have unfortunately put the *cart before the horse*, so to speak. Too often we have placed more importance on devices that create data, than on the data quality created by such devices itself, which has led us to our current predicament, whereby we have an estimated 90% of all data from Internet of Things devices never used [30], meaning decisions are based on approximately 10% of available data, which is astonishing to say the least.

A white paper published by the International Data Corporation (IDC) in 2018 informed us that we recently reached 18 zettabytes of data and by 2025 this is expected to reach a phenomenal 175 zettabytes [56]. While building related data is not anywhere near this 'Global data sphere' figure, it is still in the petabytes range and will undoubtedly require Artificial Intelligence (AI) to release its full potential.

Advances in Artificial Intelligence (AI) will, without doubt, be one of the keys to meeting these challenges and while data analytics itself is not new and has been around since databases technologies first came on the scene, digital transformation, having been highlighted as the core of the ongoing industrial revolution [17] requires the need for software applications to be rolled-out quickly to address the challenges of achieving a 40% reduction of energy use in buildings and 36% of CO2 emissions in the EU [18]. These software applications have the potential to provide greater insights into our building stock, enable quicker more qualified decisions to be made, thus reducing energy and other costs, reduce CO2 emissions, meeting EU targets and ensure greater alignment with the Sustainable Development Goals.

Crucially, greater awareness of our buildings data will lead to more accurate policy decisions, and with the availability of real-time data there is the potential to perform analysis and monitoring of policies enacted and currently underway around the EU such as the Renewable Electricity Support Scheme (RESS). The aim of this section is to provide governments with the tools to monitor and measure their initiatives and meet their individual targets.

Finally, good data about our building stock will have the potential to drive not only innovation, but Energy-as-a-Service, introducing new business models and business opportunities for several enterprises, such as hardware manufacturers, software companies and Energy Services Companies (ESCOs).

In summary, Big Data brings both opportunities and challenges, each of the 14Vs mentioned in the list above are no easy task and data scientists, engineers and analysts have an enormous task when dealing with big data and without high-quality data our potential for creating greener buildings will be even more challenging.

5 Machine Learning Application to Residential Data

In the previous section on Big Data, we introduced Artificial Intelligence (AI), Machine Learning (ML) is a subset of AI and both have a symbiotic relationship [20], i.e., they depend on each other, Big Data needs ML to extract the value and ML the volume of data to increase the accuracy of its results.

Without the use of ML, this would be a time consuming and tedious processes to complete this task, and in the majority of cases involving buildings energy related data it would lead to the data being of little or no use in op-

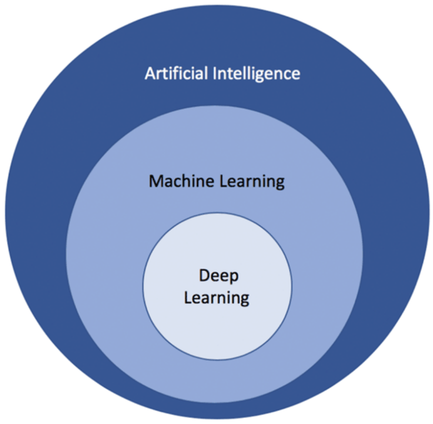

Fig. 6. Artificial Intelligence Subsets [8]

timising systems to reduce consumption, i.e. once analysis was carried out the situation (such as weather, temperature or occupancy) would have changed. It is important to extract meaningful value from the data quickly in order to create actions while they are still relevant. ML is divided into several different types, 1) Supervised, 2) Unsupervised and 3) Reinforcement Learning, each of these types have several methods (or algorithms), in the rest of this section we will discuss these types and methods and describe how they can be of use in extracting value from building energy data.

5.1 Machine Learning Algorithms

- **Linear Regression**: linear regression aims to find the best-fitting line, also referred to as the regression line [55], it is represented by the linear equation $y = mx + b$. Linear Regression is one of the most common ways of estimating real values by modelling the dependent (y) and independent variables (x). For example, heating degree days (HDD) and energy use by creating a slope (m) and intercept (b) which could form the baseline for a measurement and verification (M&V) project.
- **Logistic Regression (LR)**: whilst the name implies that it is a type of regression algorithm, it is in fact a classification algorithm. In short, LR looks at data such as 1/0, true/false, on/off etc. to predict the probability of occurrence [64]. LR can be broken down into three types: 1) Binary, 2) Multinomial and 3) Ordinal and in relation to building energy data is of particular use, for example to determine whether a window is open or closed, a piece of equipment is on or off, or if a space is occupied or unoccupied. This can be of benefit in making adjustments to heating/cooling of a space.
- **Decision Tree (DT)**: to create actions in buildings (such as HVAC) based on other factors (such as weather or occupancy), it is important to have a

method for making decisions, this is where DT comes in. As a supervised learning algorithm, DT enables, as the name suggests, decisions to be made based on if the answer to an if/else type statement is true or false, for example is it raining?, if it is raining is the window open or closed?, if the window is closed then has the space temperature increased above a specific temperature?, if it has then reduce heat to the space or increase cooling.

- **Support Vector Machines (SVM)**: SVM is a supervised learning algorithm for two-group classification problems, after plotting the data points, a best hyper-plane (decision line) is calculated, with these data points falling on either one side or the other of the data plane. Predicting energy consumption is just one of the benefits of SVM, the ability to take variables such as equipment data, sensor data, weather data, occupancy and the time of year to predict building energy consumption and performance.
- **Naive Bayes (NB)**: based on the Bayes' theorem [4] NB predicts membership probabilities for each class. This means that it determines if a data point is in one class or another. In conjunction with other algorithms mentioned previously, NB can be used in buildings to predict HVAC energy [41].
- **k-Nearest Neighbors (KNN)**: KNN is a supervised classifier, which can be used for both regression and classification and is based on the principle that data points in proximity to one another fall under the same class. It begins by classifying a value for k, for example 5 and looks for the 5 nearest neighbour to k [16]. In building energy, KNN is used, amongst other things, for predicting daily energy demand for example.
- **K-Means**: K-means applies random centroids in plotted data, it clusters data around the nearest centroid, creating an average of all points within that centroid. There are many variables that can affect energy consumption, such as occupants. Occupants are generally unpredictable and harder to create accurate models for. In building energy the ability to cluster different occupants can ehlp predict energy consumption [1] or applying behaviour recommendations to occupants with similar behaviour patterns (such as when they use electricity, arrive at or leave a building or what their preferred environmental conditions are), NB can be of particular use in such cases.
- **Random Forest (RF)**: RF gets its name from a collection of decision trees and is a particularly easy to use algorithm, although there are some differences betwen RF and DT. Similar to KNN, it can be used for both regression and classification tasks. RF starts by deciding the n_estimators hyperparameter, simply put this is the number of trees. RF can provide similar services to those mentioned previously.
- **Dimensionality Reduction Algorithms (DRA)**: DRA refers to several techniques, such as Principal Component Analysis, or PCA, and Linear Discriminant Analysis, or LDA, that are used in training data to reduce the number of input variables. As occupants spend 90% of their time indoors, it is important to ensure thermal comfort is assured, and DRA is one of the methods used to help analyse data to achieve this, by identifying significant

values from the huge quantity of data gathered and works in combination with some of the previously mentioned algorithms to achieve this.
- **Gradient Boosting algorithms (GBA)**: GRA employs the prediction of several base estimators to improve robustness over a single estimator and is used in building related energy data to take values from several weak sources to help make a better decision, for example, in cases where there are several sensors gathering information on temperature for example, GBA can help increase the confidence of the predicted temperature based on the values of all of these combined.

In summary, as described in the list above, there are several options available to data scientists and engineers, some are costly from an energy use point-of-view, or time-consuming depending on the quantity of data being processed. It is important when choosing one method over another, that we monitor the actual results of the actions taken based on such results. In the following section on Energy Modelling, we will see how the algorithms above can be used. Without ML, the extracting value from the huge volume of data being generated will be enormously challenging, even impossible for time sensitive tasks.

6 Energy Modelling

Historically, residential buildings and their occupants have played a passive role as electricity and energy consumers. Residential electricity demand could be reliably forecast at an aggregate level based on the time of year, time of day and the day of the week. The time of the year is related to weather, while occupant behaviour and usage activities are related to time of day and day of the week.

Representative load profiles are derived for similar groups of customers exhibiting characteristic diurnal pattern with morning and evening peaks [25, 47]. It is important to understand the similarities and differences between groups of customers, and to understand their coincident demand because electricity networks are designed to meet the maximum coincident demand connected at the same substation. Paatero et al. note the importance of understanding and modelling residential load for planning medium and low voltage networks in residential areas [53]. They also note the need for extensive data about consumers, their appliances and the households in general to create useful models. They describe a bottom-up statistical modelling and simulation approach based on two Finnish sets of hourly data from appliances and lighting for blocks of 1082 households, but excluding heating and cooling appliances. They fit probability density functions to the data and simulate additional load for domestic appliances to create sample load profiles for a portfolio of residential consumers.

The focus in [73] is on load patterns for consumer groups using frequency domain analysis. They analyse the average load for groups of customers in the frequency domain, noting that the individual load patterns are smoothed by taking the average over the group. They also note, that they made no attempt to re-cluster the customers in the sample. They rely on the customer class group defined by the utility company. Customer classification is important in developing demand side products suitable for the customers' needs and lifestyle.

The adoption of low carbon heating and transport technologies will drive the demand for electricity up, while distributed renewable energy sources such as solar thermal or solar photovoltaic panels will drive demand from the grid down by allowing electricity to be generated locally. There is a need to adapt electricity supply and demand forecast models taking the adoption of low carbon technologies and the potential for self consumption into account at the level of the individual home for the HEMS described in Section 3.

Short-, medium-, and long-term electricity forecasts are needed so that the grid can be operated and managed efficiently. Short-term high resolution forecasts are needed for operational purposes such as the unit commitment problems. Medium-term forecasts facilitate maintenance scheduling, while longer term forecasts and estimates of demand are needed for strategic investment and planning decisions. These forecasts are used by system operators to dimension the network to meet the maximum average coincident demand.

The objective of all forecasting is to create as accurate a forecast as possible. The accuracy of predictions decreases as the forecast horizon increases. Multiple Linear Regression is often used for medium and long term forecasting to estimate a trend based on historic demand and influenced by socioeconomic factors. For higher resolution short term forecasts additional approaches include traditional time series statistical approaches ((A)ARIMA), Machine Learning (ML) such as SAX, or Neural Network (NN) or deep learning methods.

A comparison of time series approaches to electricity forecasting is given in [46]. A machine learning artificial NN approach is used in [58], while [26] give an overview of the main methods described in the academic literature between 2005 - 2015. In all cases the time series data need to be reduced to a smaller set of explanatory variables or features without loosing important information.

The residential sector accounts for about a quarter of the energy used in Ireland. With the availability of smart meter data, individual homes or appliance can be modelled. Characterising electricity demand at an aggregate level poses different challenges to individual dwelling level [46]. The signal from an individual device or home can be noisy. Individual appliance level can be aggregated to a household, then to building, district and smart city level. Alternatively, aggregate forecasts can be created at geographic regional areas for (smart) homes connected at the same substation, or for Local or Renewable Energy Communities.

Households are heterogeneous customers that consume different amounts of electricity at different times of the day for different purposes such as heating, cooking, and electrical appliances. Understanding the timing and amplitude of the demand, and the relationship with household characteristics is important in planning production and grid capacities, and in designing policies [2].

The increased demand from homes heated by air source heat pumps (ASHPs) is explored in [7] while the real world operations of ASHPs in retrofitted homes is analysed in [6]. Multiple linear regression is used by [45] on smart meter data from consumer behaviour trials in Ireland, [9]. They explore two bottom-up approaches: a model based on dwelling and occupant characteristics that explains usage patterns for different types of households; and a model based on electrical appliances that explains how electricity is consumed. They find that time of use for maximum electricity demand is strongly influenced by occupant characteristics, such as head of household age and household composition.

An understanding at the individual household level offers opportunities to support high demand or inefficient high peak users with recommended solutions. Householders have different motivation to engage in energy efficiency measures. Many may simply wish to use greener energy, improve the efficiency and comfort of their home, or just reduce their energy costs. After "efficiency first" measures such as insulation and low wattage lighting, smart approaches can help householders to understand their usage patterns and highlight opportunities to contribute to a green energy transition. Changes to market structures, policies to achieve climate action plans, and the availability of low carbon technologies mean the role of households and buildings is changing. The availability of data, statistical and machine learning software tools, and Smart Grid infrastructure enables Smart Green Homes and creates opportunities for householders to transition from passive end user consumers of energy, to active prosumer roles - both producing and consuming energy.

Developing computationally tractable control-oriented models, which adequately represent the complex and nonlinear thermal-dynamics of individual buildings, is a significant challenge [38]. Data-driven predictive control models may replace traditional mechanistic physics-based models. The smart meter and smart device data may give a better understanding of the performance of devices in the real world in contrast to simulations or laboratory tests.

In summary, energy modelling is important to understand energy consumption from the customers' perspective, and to support their transition from a passive role to a user-centric scheme. Individual behaviours when aggregated in groups of customers represent coincident demands and impact performance and/or forecasting directly.

7 Use Cases

7.1 CENTS

The Cooperative ENergy Trading System (CENTS) framework [34], is a collaborative project coordinated by the International Energy Research Centre (IERC), Tyndall National Institute, in partnership with industry experts (e.g., Smart MPower [62] and mSemicon [48]), research organisations (e.g., University College Cork (UCC) [66], National University of Ireland Galway (NUIG) [50] and Technological University Dublin (TUD) [65]) and community energy groups associated with the sustainable energy sector (e.g., Community Power [10].

CENTS's main purpose is to deliver a blockchain-enabled Peer-to-Peer (P2P) energy trading platform, hardware requirements prototypes, and market and regulatory strategies. Additionally, through its integration platform, CENTS is capable of addressing important aspects related to energy poverty [43].

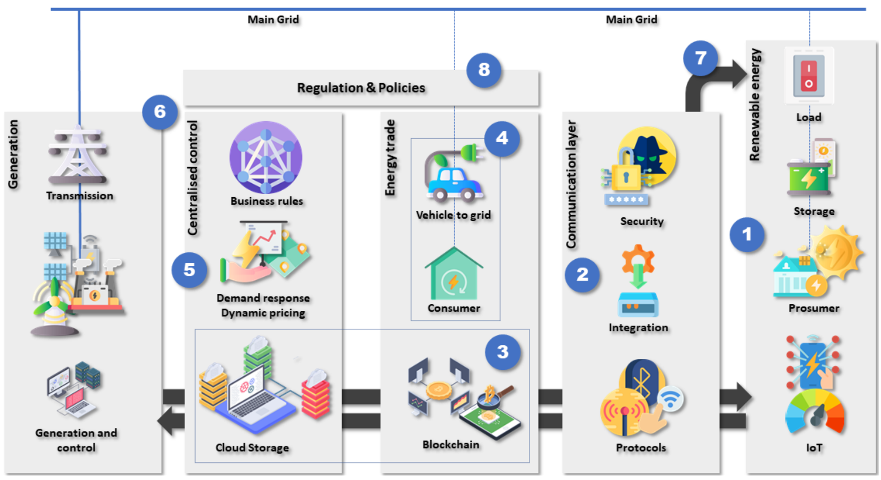

Fig. 7. CENTS high level framework [60]

Figure 7 describes CENTS high-level layered framework to address important topics for the establishment of the Smart Grid (SG) integration with green smart homes and the development of a user-centric platform of services.

At layer 1 in Figure 7, CENTS describes briefly a typical green smart home that can produce its own renewable energy and, if there is a surplus generation (remaining available energy after the household consumption took place and it is properly stored in batteries), make it available to the grid. This green smart home would be classified as a prosumer or, in other words, someone that can act as a consumer and/or a producer of energy. All sorts of IoT components (e.g., smart meters, sensors, and actuators) are at the core of the glscents platform to provide monitoring and control over the local renewable power generation and usage.

This way, glscents can provide the data to make SG integrated operation (at local, community and wider grid level). Nevertheless, such IoT apparatus lacks standardisation and the CENTS platform offers all the services necessary to integrate such a diverse range of equipment/devices, protocols, and the operation itself – including the communication and protocols issues.

In this implementation, the integration components work as a hub (concentrator) interconnecting all IoT devices and services present in the green smart home and its local distributed energy generation infrastructure to the remaining layers of the framework.

The multi-layered framework used for the CENTS project provides a decoupled architecture to guarantee faster adaptation to new scenarios, regulations and new technical demands. Most importantly, CENTS integrates prosumers, their energy production capabilities and usage profile. With the use of machine learning algorithms to define the best policies of generation, consumption and energy trading (including energy poverty policies [43], the platform can offer data-centric decision making decision and provide interaction between its functionalities and the green smart home local infrastructure.

7.2 BIM4EEB/BIMcpd

The project BIM-based fast toolkit for Efficient rEnovation of residential Buildings (BIM4EEB) [12], Figure 8, is funded by Horizon 2020 and targets the building stock renovation industry by developing a powerful Building Information Models (BIM) management system toolset to support designers in the construction planning phase and services development for building retrofitting. It facilitates decision-making and asset management (for both public and private owners) through the use of Augmented Reality (AR) and digital logbooks. BIM4EEB provides a BIM management system consisting of six tools: Fast Mapping of Buildings Toolkit, BIMeaser tool, BIM4Occupants tool, Auteras tool, BIM4EEB BIMPlanner tool, and the BIM Constraint Checking, Performance Analysis, and Data Management (BIMcpd) tool [51].

Fig. 8. BIM4EEB

BIM4EEB is a comprehensive BIM toolset and integrates data from diverse sources and partners. As discussed previously in this chapter, the data integration issue is a critical point in green smart homes integration. One of BIM4EEB's tools, the BIMcpd, delivers (amongst several other functionalities) the important task of data integration automation.

By providing the necessary toolset for data integration (e.g., file mapping and translation, and Application Programming Interface (API) integration), BIMcpd integrates data originated from residential building apartments in different sites/countries (e.g., Italy and Poland). It collects data from several sensors types and meters (e.g., energy, multisensor meters, air quality, motion detection, humidity, illuminance and temperature) and saves the data in a structured format into BIM4EEB database.

BIMcpd is capable of providing important data management functionalities to support constraint checking and performance evaluation services (e.g., BIM designer and energy auditor). By doing so, BIMcpd brings user interaction and behaviour aspects into BIM4EEB and expands its functionalities to properly develop user-centric services.

7.3 H2020: InterConnect

The use case "InterConnect" (Interoperable Solutions Connecting Smart Homes, Buildings and Grids) [19] describes one of the several projects funded by the Horizon 2020 (H2020) Framework Programme – the European Union (EU) flagship initiative for the development and maintenance of Europe's competitiveness in the global scenario (innovation, sustainable economic growth and job creation) and was supported by Europe's leaders and the Members of the European Parliament. H2020 was the biggest EU Research and Innovation programme with roughly €80 billion of funding invested in the period from 2014 to 2020.

The InterConnect project was funded under the call "Digitising and transforming European industry and services: digital innovation hubs and platforms" and targeted the integration of Renewable Energy Sources (RES) and how smart homes (including buildings) could promote energy efficiency, as it was considered by the call an essential crucial element for the flexible consumption, optimisation and integration of Distributed Energy Resources (DERs), and storage.

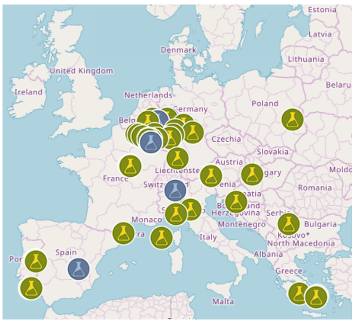

Fig. 9. Project reach

The project started on 1 October 2019 is planned to last until 30 September 2023 and had an overall budget of € 35.8 million (with an EU contribution of € 30 million). It is a pan-European project coordinated by INESC TEC (a research organisation from Portugal) [35] and with a consortium composed by other pan-European research organisations and private for-profit entities from several EU member states: Austria, Belgium, Germany, Greece, Italy, Netherlands, Poland, Serbia, and Slovenia – as illustrated in Figure 9.

The partners in the consortium are important stakeholders in the new energy paradigm represented by smart homes and smart grids revolution and comprises competencies in all key sectors (e.g., ICT, IoT, energy and data science) and relevant associations with ICT and the energy sector.

Interconnect seeks to develop an interoperable ecosystem bringing demand-side flexibility with effective advantages for the end-user. Although control over appliances is not a new concept, neither is the problem with interoperability. End-users should not be penalised (change their appliances and other interoperability issues) every time they choose to move to another technology or service provider to benefit from new technologies to improve their sustainable behaviour.

As the energy sector moves toward digitalisation and becomes more user-centric (and market-driven), the number of energy service providers increases and so does the number of improvements for monitoring and controlling – and it makes the interoperability problem even more challenging.

Interconnect is still a work in progress, but it aims to prove that it is possible to develop a digital market for the energy sector with considerable contributions of Demand-side Flexibility (DSF), more viable investments and accessible operational costs, and help the EU attain its energy efficiency goals. For that, seven large-scale pilots will be distributed in diverse countries to hit several types of end-users and green smart homes setups (appliances, services and interoperability).

7.4 Retrokit

RetroKit®[15] is a company that illustrates how green smart homes can be integrated to develop data-driven decisions and support policy-making, and guide investment in the housing stock retrofit. To do that, RetroKit®create a software-based decision-support tool to aggregate all data collected from potentially hundreds of associated smart homes – an example of the dwelling mapped is shown in Figure 10.

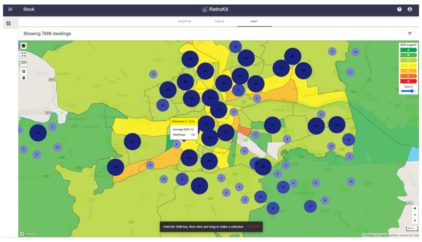

Fig. 10. Dwellings mapping

It then creates a customised database with the baseline energy performance of a housing stock, including energy use and expenditure, CO_2 emissions and Building Energy Rating (BER), Ireland's Energy Performance Certificate (PEC) rating, at the whole stock level and per relevant dwelling cohorts. RetroKit®can pull a dwelling's PEC data on behalf of its owner from the Sustainabel Energy Authority of Ireland (SEAI) BER National Administration System, allowing easy access and analysis of this data by the user. The data is then analysed to model and compare a wide range of energy renovation scenarios, helping decide the best route to meeting the user's objectives, whether these are based on budget, CO_2 emissions, the health of the homeowners or fuel/energy poverty targets.

Next, a multi-criteria analysis approach is used to identify optimal renovation scenarios considering a range of KPIs and ML algorithms automate the selection of energy renovation measures and improve scenario modelling outcomes, from the individual dwelling level to whole-stock level. This type of modelling capability will also help policy-making, at the local and national level (e.g., to support the cost-optimal energy renovation calculations according to Article 5 of the recast Energy Performance of Buildings Directive (EBPD).

With this data and knowledge, the housing stock owner can develop their energy renovation roadmap, define bespoke packages of energy conservation measures with budget estimates, funding opportunities and an action plan. This structure provides accurate evidence-based decision-making by key stakeholders supported by a mapping application that facilitates spatial planning of energy renovation in housing (e.g., for an area-based approach to project development).

Finally, local authorities and other social housing landlords can access the data to identify options to facilitate funding applications and reporting, and can integrate other datasets with its API (e.g., stock condition surveys) for improved evidence-based decision-making and planning.

In summary, a common characteristic in all use cases is the importance of the user-centric approach. Although the integration of green smart homes (both at local, community or grid level) offers significant integration challenges, the hardware (e.g., IoT and appliances) and data collection and integration is fundamental for the development of any solution targeting green smart homes in the broader carbon footprint reduction.

8 Conclusion

Green smart homes offer enormous potential to help address the carbon footprint issue and the 2030 Climate Target Plan goals. As smart home technologies evolve to encompass more household appliances, advanced sensor devices, disseminated IoT adoption, flexible integration and pervasive communication, added to their potential for DRE generation, green smart homes offer unprecedented support to user-centric and data-centric decision- and policy-making schemes.

Big data is growing at a exponential rate and this will continue to rise as we have become dependent on data for every facet of our lives, this puts huge demands on our electricity systems (data centres) and we must ensure that data is gathered and used to ensure that we reduce our energy consumption and carbon emissions. Data offers major opportunities to optimise building stock, but requires skilled data scientists, engineers and analysts, in order to extract value from big data. There are several AI techniques available and these must be used properly to ensure that they do not add to the resource demands on the electrical system, and most importantly that AI is used for good, i.e, from an ethical point of view.

The United Nations, the European Union and several global governments are committed to climate change, with several goals and targets in place. It was encouraging to see world leaders at COP26 take on the climate change challenge and it is imperative that the entire planet take on this challenge together in the same or even greater manner that it is currently doing to get a handle on the global pandemic.

Green Smart Homes are vital in helping reduce the energy consumption and carbon emissions as mentioned previously in this chapter and without machine learning we would face an uphill challenge in decarbonising global building stock.

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