Results of a literature review on methods for estimating buildings energy demand at district level

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ABSTRACT

In the framework of distributed energy planning, evaluating reliable energy profiles of different sectors has a prominent role. At the same time, it is a quite challenging task, since the availability of actual energy profiles of buildings at the district level is not widespread. A survey of over 70 studies in scientific literature has been accomplished and a set of criteria has been defined for classifying the selected contributions based on the energy demand data features, source and/or estimation methods, high-lighting the ones adopting hourly energy profiles. As final results, tables summarizing the main methods characteristics and a selection of studies providing directly useable energy profiles are reported. Therefore, this study could be useful for stakeholders involved in energy simulations of buildings stocks and community energy planning in assessing the buildings energy demand, with different desired level of detail and available data. The research, broadly, demonstrates that the potential replicability of ana-lysed methods is constrained to the datasets availability and, particularly, highlights the need of reliable hourly energy profiles definition for developing accurate energy scenarios.

Keywords:
Urban district energy planning
Distributed energy systems
Urban district energy demand estimation
Urban energy profiles estimation methods
Buildings hourly energy consumptions

1. Introduction

Cities are responsible of around 70% of global energy demand and are considered as crucial for effectively abating energy consumptions [1]. The topic is largely discussed in literature, which highlighted the large diversity of applied approaches [2,3] and the necessity to move towards the concept of smart energy system, focussing on synergies among different energy sectors [4,5]. However, considering the high responsibility of the building sector [6], this study focussed on related energy demand assessment. Indeed, among significant challenges to be tackled in the municipal energy planning, the accuracy of available energy data and tools is still an issue at several public administrations [7,8].

The transition pathway towards smart energy systems requires a combination of measures, such as integration of also intermittent and unpredictable renewable energy sources (RES) [9,10], of demand response programs [11], installation of storage devices [12], etc. This requires an accurate knowledge of the energy system for ensuring the complex hourly energy balance, which is also strictly correlated to system efficiency and costs. Therefore, considering the increasing need of accurate hourly energy profiles and, at the same time, the lack of precise information in relation to buildings stocks level, also due to privacy issue, we present a survey on studies regarding community energy planning, with the primary scope of investigating proper, proven and commonly adopted sources and methods for determining the energy demand of buildings, highlighting those which relied on hourly profiles.

2. Methodology

Based on our scientific literature research, we found over 70 among case studies of energy scenarios in urban communities and studies explicitly dedicated to the definition of hourly (or sub-hourly) energy profiles. In analysing them, the main attention was devoted to the energy demand side, in order to extract information on the origin and/or method to estimate the used data, with special regard to the time resolution.

In the context of review articles on methods for buildings energy demand estimation, the study of Swan and Ugursal [13] is one of the most exhaustive. They made a first broad distinction between:

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– Top-down methods, whose outputs data are estimated based on aggregated input data through econometric or technological correlations;
– Bottom-up methods, based on use of subordinated input data and highly detailed and reliable calculations. Bottom-up methods were in turn divided into:
  – Engineering methods, explicitly accounting for the energy consumption of end-uses, based on equipment power ratings and heat transfer laws and can be fully controlled across all calculation steps. They foresee the adoption of three alternative techniques:
    – Archetypes, energy modelling of a given building stock bases on its clustering through representative fictive buildings, leading to a computational time saving [14];
    – Samples, similar to the archetypes but with real selected buildings;
    – Distributions, usually based on statistical information of the different appliances and related usage to calculate the energy consumption of each end-use. Even if they are closed to statistical methods, Swan and Ugursal referred to them as engineering ones because of the high level of detail;
  – Statistical methods, whose outcomes come from identified statistical correlations among considered variables (e.g. energy use, weather data, occupancy behaviour, buildings' features, etc). Since they are able to deal with uncertain and random data, their use sharply grown up in last decades. They were divided in:
    – Regression, determining the coefficient of the model corresponding to the input parameters which are considered as affecting energy demand;
    – Conditional demand analysis, regressing energy demand onto the list of appliances indicated with binary or count variable;
    – Neural networks, similar to regression and inspired to the biological neural networks.

Starting from the classification reported in the aforementioned article [13], investigated studies have been hereinafter classified, consistently with the main scope of this research, first according to the time resolution of used energy demand data and then, to the adopted data source/estimation method, as follows:

– Studies adopting time-aggregated energy data (A), as:
  – Over-monthly energy data (A1);
  – Approximated energy profiles (A2), often derived from top level data;
– Studies adopting detailed energy profiles (B), as:
  – Actual consumption profiles (B1);
  – Energy profiles estimated through engineering methods (B2), in turn divided into studies using:
    – Representative buildings (B2.1), which group archetypes and samples into a single category, given their similarity as also highlighted in Ref. [15];
    – Distributions (B2.2), including studies on electricity consumption accounting through detailed characterization of occupancy and usage patterns;
  – Energy profiles estimated through statistical methods (B3); due to the increasing diffusion of statistical methods, it was necessary broadening the field compared to Ref. [13], therefore they were divided into:
    – Statistical correlations (B3.1), which refer to the simplest methods;
    – Machine Learning (ML) (B3.2).

Following, all identified classes are outlined by means of the related collected studies, which are described in terms of energy demand data source and/or estimation procedure, time resolution, end-use sector and service, spatial scale and location. Finally, studied are discussed and compared, by means also of tables summarizing the main features of the adopted methods and the represented outputs (Fig. 1).

2.1. Studies adopting time-aggregated energy data (A)

2.1.1. Studies adopting (over-)monthly energy data (A1)

In some studies, the annual or monthly energy demand was calculated, either based on engineering or statistical methods, for assessing the balance of the potential energy supply with the energy loads. Although such approach is typical of truly early stage first analysis, it clearly returns in highly approximated outcomes which can be largely far from more detailed results.

Engineering methods were used in Refs. [16–20]. In detail, the energy consumptions were calculated in Ref. [16] including the heat distribution losses in the district heating (DH) network, according to local monthly based calculation procedure for new high energy performance buildings, in Ref. [17] by means of energy simulations, assuming single thermal zones and retrieving properties from direct survey, statistical and commercial data and software libraries referring to California, in Ref. [19] by means of a simplified steady–state procedure and GIS that provides the map of the annual energy demand.

Statistical methods were used in Refs. [20–24]. In detail, consumptions were estimated thanks to statistical data on population

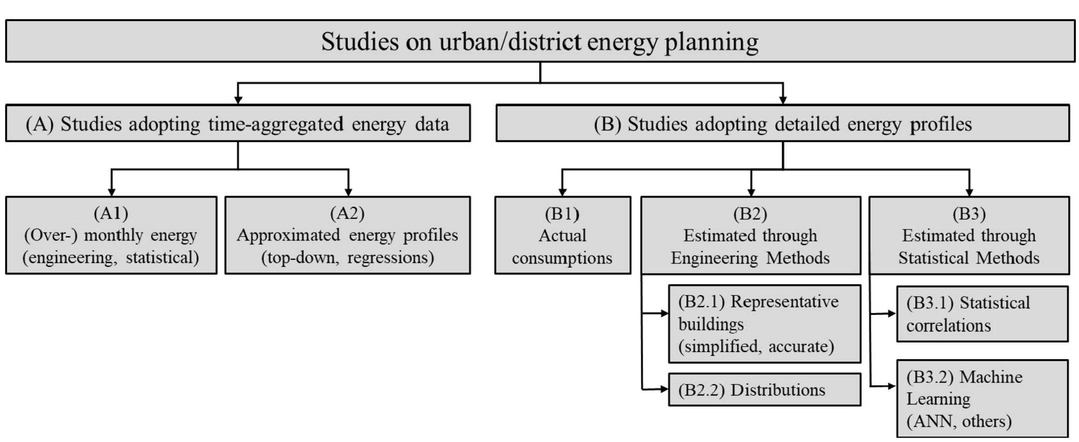

Fig. 1. Scheme of adopted classification.

and/or buildings characteristics in Refs. [20,21,23,24], while through correlations with weather data (e.g. energy signature [25]) in Refs. [21,22]. In particular, in Ref. [21] a constant domestic hot water (DHW) consumption, determined based on the buildings' typological features, was added to the monthly space heating calculated with the energy signature method. Annual consumptions were used in Refs. [17,19–21,23,24], monthly ones in Refs. [16,18,20,21] and fortnight ones were derived in Ref. [22] by weighting the annual space heating energy consumptions of representative buildings with the related heating degree days.

Regarding the energy service, electricity was assessed in Refs. [16–18,20,21,23,24], thermal energy in Refs. [16–22], transports in Ref. [20].

Regarding the investigated spatial scale, applications for small groups of buildings in California [17], districts located in Helsinki [16], Gothenburg (Sweden) [18], Belgian territory [20], Andalusian context (Spain) [21], Vercelli (Italy) [22], Oeira (Portugal) [23], Palermo (Italy) [24] and a whole town (Roncegno Terme, Italy) [19] have been found.

2.1.2. Studies adopting approximated energy profiles (A2)

In order to provide more accurate energy assessments while coping with serious lack of data, some studies adopted procedures for deriving approximated profiles from top-level data, thanks to correlations with weather data, building use category or typology consistency.

Top-down approaches were used in Refs. [26,29,30] to proportionally derive hourly profiles at local level from spatially aggregated hourly ones. In Ref. [26] the energy demand hourly profiles for a small Italian town (Corinaldo) have been derived by scaling-down the previously determined national hourly ones [27,28] to the consumptions reported in the municipal energy balance, and adjusted for considering the local climate conditions and a future scenario. Similarly, in Ref. [29] the measured national profile was scaled-down to the annual energy consumption of the Italian town of Bressanone. In Ref. [30], from the available overall urban hourly energy data, the lower scale profiles were defined, based on the distance from the urban centre (i.e. urban texture) and on the different end-use energy sector [31], for the two case studies of Helsinki and Shanghai.

Finer data can be derived also from temporally aggregated data, by means of regression. Starting data to be regressed can be obtained by means of statistical data [32,33] or simplified calculation procedures (e.g. steady state or quasi-steady state procedures, calculation based on total installed power of electric appliances, etc.) [34–41]. In particular, in Ref. [34] each building energy profiles were determined based on [42] for a representative day per each month for the downtown of Benevento (Italy); in Ref. [35], a con-stant DHW demand was added to the calculated energy demand for space heating; the energy signature method was adopted in Refs. [32,36,37] for Genève; by means of the library of scalable and randomizable so-called "synthetic" energy profiles within the Homer software [43], a stochastic regression of the calculated electric consumption was adopted in Refs. [38–40], with reference to Somaliland, Bozcaada (Turkey) and Irish context, respectively. In particular, the daily electricity consumption was scaled-up to the investigated areas in Ref. [38], based on the typical electric devices considered for a representative building, and in Ref. [39], based on the electricity consumption of a representative dwelling. With regard to Ref. [40], the residential buildings' annual space heating and DHW energy demands were calculated based on a monthly calculation procedure, the tertiary thermal energy consumption based on the statistical correlations found in Ref. [44], all buildings elec-tric consumptions from statistical correlations found in Ref. [45]. Actually, in energy planning it is quite delicate to adopt the Homer profiles because they are reported, equal for thermal and electric energy, just as an example. Regarding the time resolution of approximated energy profiles, regressions were carried out from annual/monthly data into daily ones [34,36], over-hourly [33,41] or hourly ones [30,32,35,37,37,38] while from daily data to hourly [39,40] and from regional hourly to local hourly [26,29,30]. In Refs. [33,41], in detail, 4-h resolution energy profiles for selected days representative of the year had been used, determined based on statistical correlations among measured data and weather var-iables of Greek context [46] and calculated with reference to UK context, respectively.

Regarding the considered energy services, electricity was assessed in Refs. [26,29,30,32,33,38–41] and thermal energy in Refs. [26,30,32–38,40,41].

Applications have been presented for neighbourhoods in Refs. [33,38,40], districts in Refs. [32,34–36], urban context in islands in Ref. [39], towns in Refs. [26,29,32,41] and large cities in Refs. [30,37].

2.2. Studies adopting detailed energy profiles (B)

2.2.1. Studies adopting actual energy consumption profiles (B1)

For the accurate estimation of energy fluxes, the availability of actual hourly based energy consumptions for the investigated case study is of course the optimal condition, as pointed out in Ref. [47]. Hourly data can be generally retrieved by monitoring campaigns in delimited areas, such as University campus, or provided by electricity distribution utilities or district heating networks ones.

Profiles of district heating demand were used in Refs. [29,48–57], measured electricity from utility and monitored consumers in Refs. [50,54,58,59]. Energy demand was collected for University campuses in Espoo (Finland) and Trondheim (Norway)[50,55], districts in Osimo (Italy) and Linkoping (Sweden) [48,49], an urban context within Greek island of Lesbos [58], cities of Bressanone (Italy), Frederikshavn (Denmark), Aalborg, Turin and Stockholm, Popusko (Croatia) [29,51–57] and for Portuguese context [59].

Profiles as input data for the EnergyPLAN software [60] were used in Refs. [29,51–54]. In Refs. [54,55] the registered profiles were also adjusted for foreseeing the effects of energy scenarios, such as buildings energy efficiency measures (EEMs) and different level of occupancy. In Ref. [57], the profile for the assessed city was not available so the one from a closed city was adjusted to the total heat consumption.

2.2.2. Studies adopting energy profiles estimated through engineering methods (B2)

Engineering methods are also named *physical*, since are founded on the detailed assessment of processes through physical laws, merely the building's thermal energy balance and the electric appliances consumption, *deterministic*, since from given inputs certain outputs are derived, or *white-box* methods, since the user is able to fully control their execution. The adoption of engineering methods to assess the energy demand of buildings enables to have very accurate estimations, when based on dynamic energy simulation. Despite this, detailed building energy simulations on urban scale could not be always time sustainable due the required level of detail and quantity of information, therefore simplifications in the calculation methods or in the number and complexity of the modelled buildings are often adopted.

The following studies adopted "*Representative buildings*" (B2.1). Simplified calculation procedures for deriving buildings thermal energy profiles were used in Refs. [61–66]. In detail, in Ref. [61] with reference to Beijing, a simplified method was developed for the prediction of buildings hourly cooling loads, to be applied on large-scale urban planning, which bases on linear correlation between cooling load components of the thermal balance and environmental parameters such as temperature and enthalpy differences. In Ref. [62] a simplified method was developed for heating, ventilation, air conditioning (HVAC) load estimation, assuming only one thermal zone building, neglecting internal gains and considering average solar radiation among exposures; the application of the method to a group of ten archetype buildings was reported. The EN ISO 13790 simplified hourly method [67] was adopted in Refs. [63–66]. In particular, in Refs. [63,64] a hybrid procedure was defined, made of space heating/cooling profiles calculation for building archetypes defined for the Swiss context and their calibration with statistical data; in Ref. [65] buildings archetypes were defined with reference to a district in Manhattan and based on the DOE Commercial Prototype Buildings dataset [68] and the calculation method was corrected for considering buildings shadowing, urban heat island effects and occupancy.

More accurate estimations of thermal energy profiles, by means of detailed dynamic building energy simulation tools, such as TRNSYS [69], EnergyPlus [70], ESP-r [71], etc., have been carried out in Refs. [72–82].

Within accurate studies, some of them were aimed at determining profiles for representative buildings. In particular, in Ref. [73] profiles of space heating and cooling for a parameterized office building representative of the UK building stock; in Refs. [78,79,82] of space heating for multi-thermal zones residen-tial/office archetypes (defined based on different building sizes, envelopes, occupancy patterns and HVAC technologies) for the Austrian context; in Ref. [80] of space heating and cooling for multi-thermal zones residential/office archetypes (defined based on different geometry and envelope solutions) for several locations in Italy; in Ref. [81] of space heating and cooling for residential/office archetypes (whose occupancy profiles were based on the recent prEN 16798-1 [83] and ISO 17772-1 [84] standards) placed in Finland.

In detail, in order to associate to a building stock the hourly energy profiles simulated for the representative buildings, in Refs. [78,79] they were converted to profiles in percentage values referred to the annual consumptions, while in Ref. [80] they were compared to the buildings' volume obtaining energy profiles per built cubic meter.

Based on representative buildings, samples or archetypes, application studies on district and city scale are reported for Turin [72], a community in California [74], Zurich [75], a Swiss small town [76,77] and an Austrian town [82], respectively. In particular, in Ref. [72] samples were clustered according to age, typology and then, their simulated profiles were associated to district real buildings through a stochastic-random association procedure; in Ref. [74] the archetypes were defined according to the DOE Com-mercial Prototype Buildings dataset. Regarding the accurate esti-mation of hourly electricity consumption, in some studies profiles were determined based on archetypes [63,64,85,86], samples [76,77,87] and statistical data [88].

In particular, in Ref. [85] residential and office archetypes in Italy were developed based on usage profiles from the Swiss standard [89], which was also adopted in Refs. [63,64] to define the representative buildings for the application at district scale; in Ref. [86] a representative building, equipped with alternative supply units, was modelled according to the German standard [90]; hourly electricity loads of small communities in US were simulated by defining the kind of appliances based on real case study data in the study of [87] and statistical data in Ref. [88].

Concerning the methods "*Distributions*" (B2.2), detailed data on the occupancy patterns, the kind of electric equipment and use and the energy consumptions, can be retrieved from comprehensive time of use surveys, statistical information or actual measurements. Examples of this method can be found for applications in UK [91–94], Japan [95,96], Denmark [97], Sweden [98], Spain [99] and Germany [100]. In particular, in Ref. [91] it was developed a model for generating electricity profiles for dwellings integrating a previous model for 1-min resolution artificial lighting profiles [92], based on irradiance actual measurements, industrial product data and considering daylight, co-use of lighting and frequency of use. In Refs. [95,96] occupancy and activity profiles were first defined based on statistical information and time of use survey across Japanese population and then, by crossing them with information on appliances type and usage, household electricity profiles were generated. Applications up to the regional level were also tested. More in detail, in Ref. [94] the authors classified the electric appliances by three levels of power and nine levels referred to frequency of use; in Ref. [98] by three usage modes referred to base load (e.g. refrigerator), time-related load (e.g. TV) and variable load (e.g. artificial lighting).

2.2.3. Studies adopting hourly energy profiles estimated through statistical methods (B3)

Statistical methods are also named *data-driven* or *black-box* methods, since the correlation among inputs and outputs is not always straightforward and is derived by assuming weights and bias. Despite a lower detail for the single data than in the engineering methods is required, their use allows to cope with data uncertainty, randomness and lack, therefore their application is suitable for prediction of stochastic phenomena, like consumers behaviour. Since the recent increasing diffusion of statistical methods in building physics related research and applications, several techniques nowadays are adopted, as described in the following.

The following studies adopted the "*Statistical correlations*" (B3.1).

Typical examples of Statistical correlations are reported in Refs. [101–108]. In detail, space heating and cooling, DHW and electricity consumption profiles were determined based on statis-tical analysis on data from direct survey and measurements overall Korea for department stores in Ref. [101], hotels, hospitals and office buildings in Ref. [102]; space heating profiles average per season were determined in Ref. [103] for residential, tertiary and industrial buildings based on measured DH consumptions in Sweden; in Refs. [104,105], for the six single-family houses case study, adopted electricity hourly load profiles were based on the ADRES-CONCEPT Austrian database [109], whose profiles have been determined for a set of building typologies and day-types since direct surveys and measurements; in Refs. [106,107], hourly profiles of electricity, through probability distribution function, based on measured data in Trondheim (Norway), were determined for several building typologies, differing by use category (residen-tial, office, educational, hospital, hotel, sports, retail), age and size; in Ref. [108], electricity profiles for the Sao Paulo end-use sectors were determined by means of probability distribution. With regard to the study [101], the overall electricity consumptions have been correlated with weather data in order to disaggregate the share due to appliances and artificial lighting from the one due to HVAC systems.

Studies explicitly referred to regression analysis are reported in Refs. [106,107,110,111]. In particular, hourly profiles of space heating, through regression analyses of measured energy consumptions and outdoor temperatures, were determined for different building archetypes, defined in terms of period of construction and use category in Refs. [106,107]. In Ref. [110], based on historical data of DH consumption and weather data for the Swedish town of

Eskilstuna, computed regression coefficients were applied to a Test Reference Year climatic data file in order to define a normalized heat load profile; then, for testing effects of a set of EEMs, heat demand profiles were dynamically simulated, and the daily difference was computed. In Ref. [111] a piecewise linear function between consumptions and outdoor temperatures plus a component dependant on consumers behaviour was defined and applied to predict the hourly heat load for two DH networks in Stockholm.

Regarding the considered energy services, thus, electricity was assessed in Refs. [101,102,104–108] while thermal energy in Refs. [101,102,106,107,110,111]. Applications in urban areas have been considered in Refs. [106–108,110,111].

"*Machine Learning*" methods (B3.2) are increasingly adopted for forecasting energy loads due to the ability of learning from past behaviour so returning in most robust outcomes.

Among ML methods, Artificial Neural Networks (ANN) are one of the most commonly adopted [112–114]. In Ref. [112] the authors presented a method for forecasting district heating and cooling loads, with the aim of improving previous tested ANN-based method predictions in periods affected by high fluctuations; past heat loads, as well as the day-type, the highest and lowest air temperatures of the predicted day were used as input data. In Ref. [113] after a comparison of some linear and nonlinear models, using past recorded weather data, occupancy data and hourly average measured energy consumptions as inputs, a method for estimation of day-ahead space heating, space cooling and electricity loads for a University campus in Austin (Texas) has been proposed. In Ref. [114] an unsupervised and supervised ANN based method was presented for the electric energy demand forecasting with a prediction time of one day. Input data were dry bulb temperature, relative humidity, global solar radiation, recorded electricity consumptions in a district of Palermo (Italy).

Besides, other methods than ANN have been adopted in literature. In Ref. [115] a Support Vector Machine was developed for short-term predicting the heat loads of DH connected consumers based on collecting the real data from a heating substation in the Serbian city of Novi Sad; in Ref. [116] an adaptive neuro-fuzzy inferences system model to forecast DH single consumers, based on real consumptions from a Serbian DH station; in Ref. [117] a Case-Based Reasoning method for short-term predicting the electricity hourly energy demand of tertiary buildings, based on real and simulated data of an office building, on outdoor air temperature and relative humidity in the Canadian city of Varennes.

3. Results and conclusions

For accomplishing reliable distributed energy planning, adopting detailed energy demand profiles is essential. However, it is possible outlining a general unavailability of detailed consumption profiles at local level. Based on a literature research on over seventy studies regarding urban energy planning, which is summarized in the present review article, we reported a selection of the main calculation methods for determining the energy demand of building clusters. Hence, valuable information on limitations and strengths of existing methods, allowing to choose the more suitable one based on desired level of detail and on available data, is provided while main features of mentioned approaches are summarized in Table 1 and Table 2.

From this research we saw that the studies relying on time aggregated energy data (A) often lead to the accomplishment of truly approximated estimation.

In fact, the adoption of seasonal energy data (A1) is responsible of neglecting energy fluctuations which are relevant when planning smart and RES integrated energy systems, including storage systems assessment. Moreover, approximated energy profiles (A2) derived from spatially aggregated data through top-down approach, by putting on the same level a small community and a Country, or from temporally aggregated data through regressions based on the outdoor temperatures, neglecting other weather parameters, such as the solar radiation [118], or building usage patterns, which are usually responsible of a more variable profile, can be also critical.

Regarding the studies adopting detailed energy profiles (B), apart from those cases where actual consumption profiles are available (B1), robust methods for the estimation of reliable profiles, engineering (B2) or statistical based (B3), must be chosen.

For reducing the computational effort of engineering modelling, the clustering of a building stock in a series of representative buildings (B2.1) is a well-established approach that allows, if combined with accurate dynamic energy simulations, maintaining an acceptable approximation of the energy evaluations; however, a critical point of these studies could be the assumption of standard values of the building usage patterns instead of an accurate assessment [119]. Studies adopting distributions (B2.2), which are based on statistical approach but detailed as the engineering ones, could be a way to overcome this issue.

Among the statistical methods, the machine learning based ones (B3.2) enable to reliably estimate uncertain data and even reduce computational effort, overcoming the limitations of the basic statistical correlations (B3.1). However, statistical methods adoption relies on measured/simulated data which are not everywhere accessible.

Table 3 reports an additional outcome of this survey, i.e. selected articles of studies reporting hourly profiles that could be directly

Table 1
Assessed energy service and spatial scale of investigated studies.

Class	Energy service	Spatial scale	References
(A)	electric	neighbourhoods districts	[17,33,38,40]
		cities	[16,18,20,21,23,24,32]
		neighbourhoods districts	[26,29,30,32,39,41]
	thermal	cities	[17,33,40]
		(representative buildings)	[16,18,20–22,32,34–36]
		neighbourhoods districts	[19,26,30,32,37,41]
(B)	electric	cities	[85,86,91–102,104–107,117]
		(representative buildings)	[50,75–77,87,88,113]
		neighbourhoods districts	[63,114]
		cities	[54,58,76,108]
	thermal		[61,73,78,80,81,101–103,106]
			[50,62,66,74,75,113]
			[48,49,55–57,63,65,72,110–112,115,116]
			[29,51–53,76,82]

Table 2
Characteristics of the adopted energy demand data among investigated studies.

Sub-class	Energy Calculation Method	Output Time Resolution	References
(A1)	(Over-) monthly (Engineering)	Annually	[17,19]
		Monthly	[16,18,20]
	(Over-) monthly (Statistical)	Annual	[20,21,23,24]
		Two weeks	[22]
(A2)	Approximated profiles (Top-down)	Hourly	[26,29,30]
	Approximated profiles (Regression)	Daily	[34,36]
		(Over-)hourly	[32,33,35,37,41]
		Hourly	[38–40]
(B1)	Actual consumption	Hourly	[29,48–59]
(B2.1)	Representative buildings (Simplified)	Hourly	[61–66]
	Representative buildings (Accurate)		[63,72–82,85–88]
(B2.2)	Distributions	Hourly	[91–100]
(B3.1)	Statistical correlations	Hourly	[101–106,108]
		(sub-)Hourly	[106,110,111]
(B3.2)	Machine Learning (ANN)	(sub-)Hourly	[112–114]
	Machine Learning (Others)	(sub-)Hourly	[113,115–117]

Table 3
Selection and characteristics of typical energy profiles.

Outputs representation	Time Horizon	Time Resolution	U.M.	Energy Service	End-use sector	Location	References
values	1workday + 1weekend day	1 h	W/m^2	EH	R/T/C	Norway	[106,107]
profile		1 h	%				
profile	1day + 1year	15min-1hour	kW	EHW	R	Germany	[66,100]
profile	1workday + 1weekend day per month	1 min	W	E	R	UK	[91,92]
histogram	1day	4 h	W/m^2	EHW	R/T	UK	[41]
profiles			%				
profile + values	1day per season	4 h	kW	EH	R	Greece	[46]
histogram + values	1year	1 month	MJ/m^2	EHCW	T/C	Korea	[101,102]
profiles	1day	1 h	%				

Legend – R/T/C: residential/tertiary/commercial building; E: electricity; H: space heating; C: space cooling.

adopted, or considered for comparison with own data, in further applications. To better define the boundary of their reproducibility, for each of them we indicated, beside the type of data representation, the time horizon and resolution, the energy service, the end-use sector and the location. In some case the hourly profiles are expressed as percentages to be applied to a peak power value. In particular, it should be highlighted that articles related to studies [66,91,92,100] report web-links for accessing free tools for profiles generation.

Summarizing this last outcome, given that the direct use of selected profiles is limited to similar conditions, in terms of location, end-use sector and energy service, we can also highlight that the available data are referred to some representative days of the year, so the overall variations within the long periods are not comprehensively considered (e.g. weekly, seasonal or, as required by some energy planning tools, annually based data). Therefore, further developments in research on smart urban energy planning should deepen this issue.

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Nomenclature

ANN	Artificial Neural Network
DH	District Heating
DHW	Domestic Hot Water
EEM	Energy Efficiency Measure
HVAC	Heating, Ventilation, Air Conditioning
ML	Machine Learning
RES	Renewable Energy Sources

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