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ITU-T Focus Group on Environmental Efficiency for Artificial Intelligence and other Emerging Technologies (FG-AI4EE)

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Requirements on energy efficiency measurement models and the role of AI and big data

Working group 2 – Assessment and Measurement of the Environmental Efficiency of AI and Emerging Technologies Working Group Deliverable

Focus Group Technical Report

Technical Report ITU-T FG-AI4EE D.WG2-03

Requirements on energy efficiency measurement models and the role of AI and big data

Summary

Several assessment models have been introduced to calculate the urban energy system and to demonstrate the variants that calibrate the local energy efficiency. This Technical Report focuses on the impact of artificial intelligence (AI) and big data on energy efficiency. More specifically, this Technical Report identifies a model that can calculate the energy efficiency in an urban space, from an AI and big data perspective. A literature analysis is performed with regard to the identification of existing energy efficiency assessment models under the lens of AI and big data and a special focus on the urban system, which results in an AI taxonomy for energy efficiency and in corresponding jobs (process steps) where big data are involved. This Technical Report aims to unveil the requirements for energy efficiency assessment, and the features that affect the energy demand. This Technical Report attempts to define a unified assessment model for energy efficient cities.

Keywords

AI, assessment, big data, emerging technologies, energy efficiency, models, smart and sustainable city.

Note

This is an informative ITU-T publication. Mandatory provisions, such as those found in ITU-T Recommendations, are outside the scope of this publication. This publication should only be referenced bibliographically in ITU-T Recommendations.

Change log

This document contains Version 1 of the ITU-T Technical Report on "Requirements on energy efficiency measurement models and the role of AI and big data", approved at the ITU-T Study Group 5 meeting held online, 11-20 May 2021.

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1 Scope

Energy efficiency is a crucial issue for the sustainability of cities, today and in the future, especially due to the emerging appearance of smart cities (SC) and of cutting-edge technologies. Some emerging technologies, such as artificial intelligence (AI), big data, edge computing and cryptocurrency may not take sustainability into consideration during their development. These technologies often require a huge amount of energy, resulting in significant environmental footprints. It is important to understand how to enhance the energy efficiency of these technologies in the urban space and to think of means to reduce the environmental footprint of these technologies (ITU, 2019a). In this regard, the definition of the appropriate model that can evaluate the energy efficiency of these emerging technologies is crucial, especially within the urban space and under the lens of their standardization requirements. More specifically, these technologies have to comply with the requirements of a city's energy system and with the planning for a city's sustainable future. Thus, this Technical Report aims to investigate the appropriate models to evaluate urban energy efficiency with a special focus on the emerging adoption of AI and big data.

2 Abbreviations and acronyms

This Technical Report uses the following abbreviations and acronyms:

AI	Artificial Intelligence
B5G	Beyond 5G
BEPG	Building Energy Performance Gap
CCHP	Combined Cooling, Heat and Power
CPS	Cyber-Physical System
DRL	Deep Reinforcement Learning
DVMN	Data Volume of the Mobile Network
ECMN	Energy Consumption of the Mobile Network
EEI	Energy Efficiency Indicator
EEMN	Energy Efficiency of the Mobile Network
EER	Energy Efficiency Ratio
EnSoS	Environmental and Social Sustainability
ICT	Information and Communications Technologies
IDB	Industrial Big Data
IoMT	Internet of Medical Things
KPI	Key Performance Indicator
LCA	Life Cycle Analysis
LPLA	Low Power Local Area

LPWA	Low Power Wide Area
MN	Mobile Network
MPI	Malmquist Productivity Index
PSU	Power Supply Unit
PUE	Power Usage Effectiveness
SC	Smart City
SEE	Site Energy Efficiency
TFEE	Total-Factor Energy Efficiency
TSA	Total Site Analysis
UAV	Unmanned Aerial Vehicle
ZEB	Zero Energy Building

3 Terms and definitions

3.1 Terms defined elsewhere

This Technical Report uses the following terms defined elsewhere:

3.1.1 efficiency (Cambridge Dictionary): The good use of time and energy in a way that does not waste any of them.

3.1.2 efficiency (Business Dictionary): The comparison of what is actually produced or performed with what can be achieved with the same consumption of resources (money, time etc.).

3.1.3 economic efficiency (Australian Government Productivity Commission (2012)): It is attained when individuals in society maximize their utility, given the resources available in the economy.

3.1.4 energy ITU-T L.1315: The capacity for doing work. In the telecommunication sector the primary source of energy is electricity, and it is measured in Joules.

3.1.5 energy carrier ISO/IEC 13273-1:2015: The substance or medium that can transport energy.

3.1.6 energy source ISO/IEC 13273-1:2015: Material, natural resource or technical system from which energy can be extracted or recovered.

3.1.7 energy consumption ISO/IEC 13273-1:2015: The quantity of energy applied.

3.1.8 energy intensity ISO/IEC 13273-1:2015: The total energy consumption per unit of economic output.

3.1.9 energy management system ISO/IEC 13273-1:2015: A set of interrelated or interacting elements to establish an energy policy and energy objectives, as well as the processes to achieve in those objectives.

3.1.10 energy policy ISO/IEC 13273-1:2015: The statement by the organization of its overall intentions and direction of an organization related to its energy performance, as formally expressed by its top management.

3.1.11 energy system ISO/IEC 13273-1:2015: A system that consists of all the components related to production, conversion, delivery and use of energy.

3.1.12 energy system models ISO/IEC 13273-1:2015: Conceptual tools that depict the structure and support the calculation of the technological performance and decision making for design, operation and control.

3.1.13 energy efficiency ISO/IEC 13273-1:2015: The ratio or other quantitative relationship between an output of performance, service, goods or energy, and an input of energy.

3.1.14 energy efficiency indicator ISO/IEC 13273-1:2015: The value indicative of the energy efficiency.

3.1.15 energy efficiency improvement ISO/IEC 13273-1:2015: An increase in energy efficiency that comes from technological, design, behavioural or economic changes.

3.1.16 energy performance ISO/IEC 13273-1:2015: Measurable results related to energy efficiency, energy use and energy consumption.

3.1.17 energy efficiency mechanism instrument ISO/IEC 13273-1:2015: The means that are used to create incentives or a supportive framework for market actors to follow an energy efficiency improvement programme or to provide energy efficiency services.

3.2 Terms defined here

This Technical Report defines the following terms:

3.2.1 electrical energy efficiency: The output of a device that is generated by a provided amount of power; the percentage of total energy input to a machine or equipment that is consumed in useful work and is not wasted as useless heat.

3.2.2 ICT energy efficiency: The ratio of energy consumed by specific ICT systems to the output produced or service performed by these systems.

3.2.3 city's energy system: The definition of consumers and production sources within the urban space and the estimation of their roles and importance.

4 Background

4.1 Calculating energy efficiency

In the context of electricity use, the energy efficiency ratio (EER) expresses the *output of a device that is generated by a provided amount of power*, which can be visualized in the following formula (1) ITU-T L.1315 (2017):

$$EER = \frac{Energy_{output}}{Energy_{Input}} \tag{1}$$

An alternative to the above definition could be *the percentage of total energy input to a machine or equipment that is consumed in useful work and is not wasted as useless heat* and it can be visualized with formula (2) ITU-T L.1315 (2017):

$$EER = \frac{Energy_{forUsefulWork}}{Energy_{TotallyUsed}} \tag{2}$$

The above formula (2) can be utilized for all the types of devices that use electrical power and in this regard, it can also calculate the energy efficiency of information and communications technologies (ICT) devices, which are analysed in hierarchical order in solution/network; system/equipment; and component levels ITU-T L.1315 (2017).

Formula (3) describes the corresponding energy efficiency, where *Tidle* is the throughput in idle mode in which the power is *Pidle* (ITU, 2017).

$$EER = \frac{0.6*Tidle+0.3*Tlowpower+0.1*T\int maximum}{0.6*Pidle+0.3*Plowpower+0.1*P\int maximum} \tag{3}$$

ITU-T L.1330 (2015) defines metrics for telecommunication mobile networks and associates the mobile network's energy efficiency with user population, network density and climate conditions:

$$ECMN = \Sigma i(\Sigma k ECBSi,k + ECSIi) + \Sigma j ECBHj + \Sigma i ECRCl \quad (4)$$

where:

- *EC* is energy consumption (in Wh over a specific time period (T))
- *BS* refers to the base stations in the mobile network MN
- *BH* is the backhaul providing connection to the BSs in MN
- *SI* is the site infrastructure (rectifier, battery losses, climate equipment, tower mount amplifier (TMA), tower illumination, etc.)
- *RC* is the control node(s), including all infrastructure of the RC site
- *i* is an index spanning over the number of sites
- *j* an index spanning over the number of BH equipment connected to the i sites
- *k* is the index spanning over the number of BSs in the i-th site
- *l* is the index spanning over the control nodes of the MN.

ITU-T L.1302 (2015) assesses the energy efficiency of data centres, which are affected by the ICT equipment (e.g., computing, storage and network equipment etc.) and the installed infrastructure that supports this ICT equipment's operation (e.g., power delivery components and cooling system components). The corresponding energy efficiency measurement methodology respects both load and environmental conditions, that considers the data centre's performance during busy and idle hours, and all annual seasons respectively. The data centre's devices are classified in low (LV), medium (MV) and high (HV) voltage and indicative structures are provided for developers. Some useful energy efficiency KPIs concern the *power usage effectiveness (PUE)* that is calculated with formula (5):

$$PUE = \frac{E_{DC}}{E_{IT}} \quad (5)$$

where E_{DC} represents the energy consumption of the data centre and E_{IT} expresses the energy consumption of all the ICT equipment input terminals in normal working conditions. Since the collection of this information is hard, this energy consumption is calculated with formula (6):

$$E_{IT} = E_{AR} * \eta_{IT-PDU_{efficiency}} \quad (6)$$

where, PDU is power distribution units in the data centre and $\eta_{IT-PDU_{efficiency}}$ can be calculated by measuring the voltage drop from array cabinet (E_{AR}) to ICT rack. The calculation of E_{DC} depends on the structure refer to Figure. 2 of ITU-T L.1302, of the data centre and the corresponding Recommendation ITU-T L.1302 (ITU, 2015) provides two alternatives (high/medium voltage (HV/MV) and low voltage (LV)). In both cases, the calculation is based on formula (7) and it is analysed in specific points of energy inputs (e.g., energy grid, energy generators etc.) and potential energy transformers or inverters.

$$E_{DC} = \sum_{i,j} \frac{E_i}{\eta_j} \quad (7)$$

where E_i expresses the energy consumption of specific data centre's points (i) of measurement, and η_j represents the energy efficiency of specific points (j) of measurement. The assessment process covers the entire year running conditions of the data centre.

The above analysis can result to a definition for *ICT systems' energy efficiency*, which is expressed by the ratio of energy consumed to the output produced or service performed. These models respect the synthesis and structure of the examined systems and they consider several parameters respectively (e.g., climate conditions, coverage, use, etc.).

Traditionally, energy efficiency is associated with demand control and energy savings, in an attempt to deal with the energy problem: *cover the radically emerging energy demand, with means that manage cost and other risks* (Giacomelli, 2009). Reducing energy demand is a high priority concern for many countries and is approached by both financial measures (i.e., taxation) and technical solutions (i.e., by improving the efficiency of energy-consuming products and processes) for both the demand and the supply side of the energy equation (IEA, 2014).

The city's energy system consists of the consumers and the production sources within the urban space and it is affected by both their roles and importance. Several models can be found in literature that evaluate the efficiency of a city's energy system. The *total-factor energy efficiency (TFEE) index* (Hu and Wang, 2006) was developed based on the local gross domestic product (GDP); while the *Integrated MARKAL-EFOM System (TIMES)* is based on a linear programming (LP) model approach (Loulou and Labriet, 2008; Loulou, 2008; and Anthopoulos et al., 2016). The TIMES model examines energy flows (see Figure 1) and consists of indices that refer to the region *(r)*; the calculation period *(t)*; the reference *(v)* (vintage) year; the process *(p)* (technology); the time-slice *(s)* (normally an annual calculation); and commodity *(c)* (energy, material, emission and demand). In each of the examined time periods, the production by a region plus imports from other regions of each commodity must balance the amount consumed in the region or exported to other regions, which is labeled *TIMES equilibrium*. A complete scenario for the TIMES model consists of four types of input: *energy service demands, primary resource potentials, a policy setting*, and the *descriptions of a set of technologies*. Efficiency in TIMES is targeted during the processes, where an input commodity group (cg1) passes flow to an output commodity group (cg2) and the modeler chooses a value for the efficiency ratio (*FLOFUNC(p, cg1, cg2)*) (function (8)).

$$\begin{aligned} &SUM\{c \text{ in } cg2 \text{ of} : FLOW(r,v,t,p,c,s)\} = \\ &= FLOFUNC(r,v,cg1,cg2,s) * SUM\{c \text{ within } cg1 \text{ of}: \\ &\qquad COEFF(r,v,p,cg1,c,cg2,s)*FLOW(r,v,t,p,c,s)\} \end{aligned} \tag{8}$$

(8) (Loulou, 2008)

where:

- *COEFF(r,v,p,cg1,c,cg2,s)* respects the harmonization of different time-slice resolutions of the flow variables
- *FLOW(r,v,t,p,c,s)* expresses the quantity of commodity *c* consumed or produced by process *p*, in region *r* and period *t* (optionally with vintage *v* and time-slice *s*).

The models referenced above indicate how energy efficiency is approached in cities but, they do not focus on specific emerging technologies or systems. In this regard, the methodology approach followed in this work includes a detailed and systematic review on pertinent literature, mostly focusing on recent studies that explore energy efficiency metrics and models, as well as the impact that the specified technologies (AI and big data) may have on urban energy system performance.

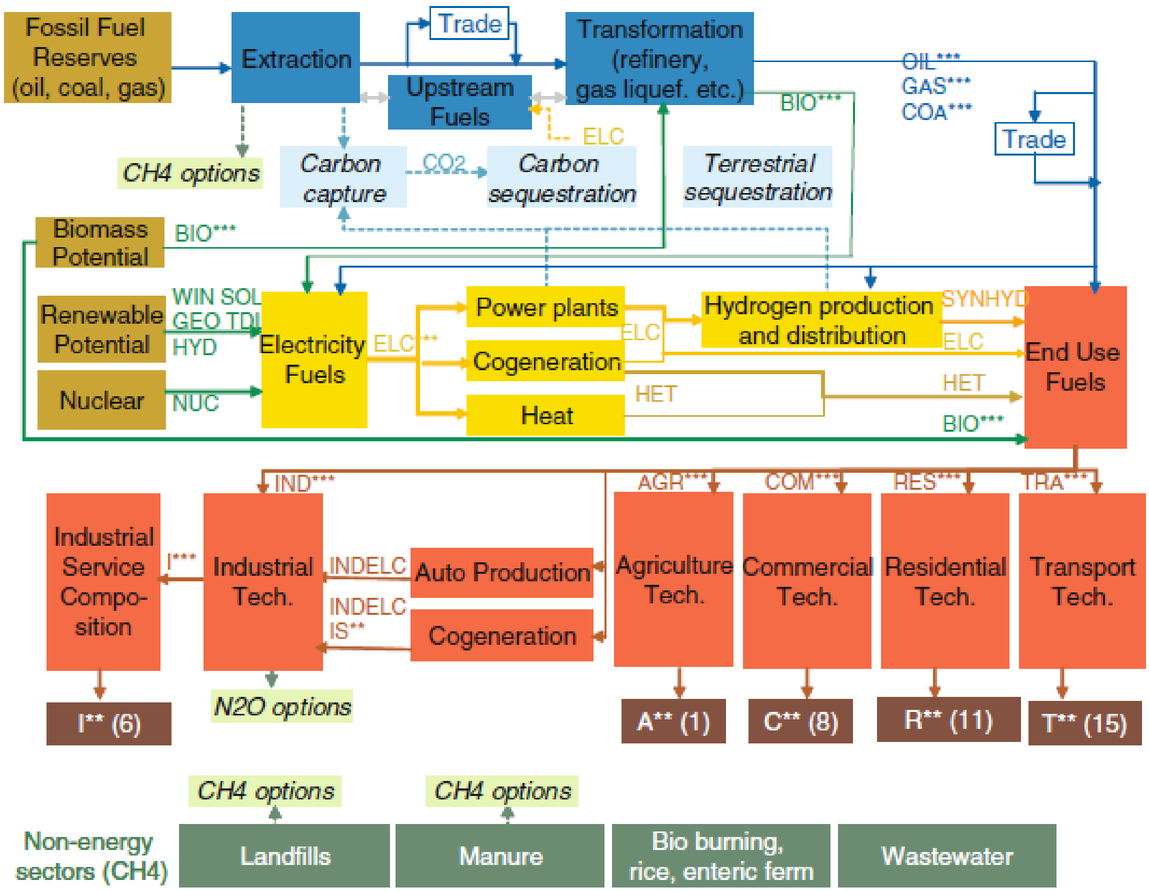

Figure 1 – TIME's sketch for the energy flows within an energy system (Loulou and Labriet, 2008)

4.2 The role of artificial intelligence in energy efficiency

Artificial Intelligence (AI) can be defined as a *computerized system that uses cognition to understand information and solve problems*. [b-ISO/IEC 2382] defines AI as "interdisciplinary field, usually regarded as a branch of computer science, dealing with models and systems for the performance of functions generally associated with human intelligence, such as reasoning and learning". In computer science AI research is defined as *the study of "intelligent agents": any device that perceives its environment and takes actions to achieve its goals*. This includes pattern recognition and the application of machine learning and related techniques. AI is the whole idea and concepts of machines being able to carry out tasks in a way that mimics the human intelligence and would be considered "smart". Several other definitions, which are close to the above can also be located in literature, such as *the use of computers to process information and to make decisions using human-like intelligence* (Meister, 2020; Cobanoglu et al, 2021). AI can be seen as an accelerator, which delivers the right intelligence in the right moment and achieve personalization at scale (Meister, 2020). AI consists of several technologies (see Figure 2) that enable devices/computers to gather data -from sensors, mobile devices and repositories- (including but not limited to speech recognition), to analyse and understand the information collected (through natural language processing), to make informed decisions or recommend action (*expert systems*), to learn from experience (*machine learning*) and to respond based on the needs of the situation (*robotics*) (Liu et al., 2017). This approach aligns better to the smart city (SC) context, where the Internet of things (IoT) plays crucial role in enabling and delivering smart services.

Figure 2 – A Venn diagram showing the AI category and subcategories (Etaati, 2019)

The roles that AI can undertake, can be summarized as inTable 1 (Boden, 1996). These key-roles could be deployed in SC in order to automate services that are based on IoT data collection and processing. As such, an AI functional model can be generated (see Figure 3), which depicts how AI works and executes IoT-based processes (see Figure 4).

Table 1 – Key-roles of AI

AI key-roles	Description
Perception	Acquire ontological information[1] (OI).
Cognitive	Convert information to epistemological information (EI)[2].
Decision-making	Convert EI to intelligent strategy (IS) aimed at problem solving.
Execution	Convert IS into intelligent action (IA) and strategy optimization. Strategy optimization respects previous errors and helps the system to avoid making them again.

1 This refers to the information on the state and pattern of variance presented by the object/device in the environment.

2 This refers to the information perceived by the subject about the trinity of the form (syntactic information), content/meaning (semantic information), and utility/value (pragmatic information) concerning the OI.

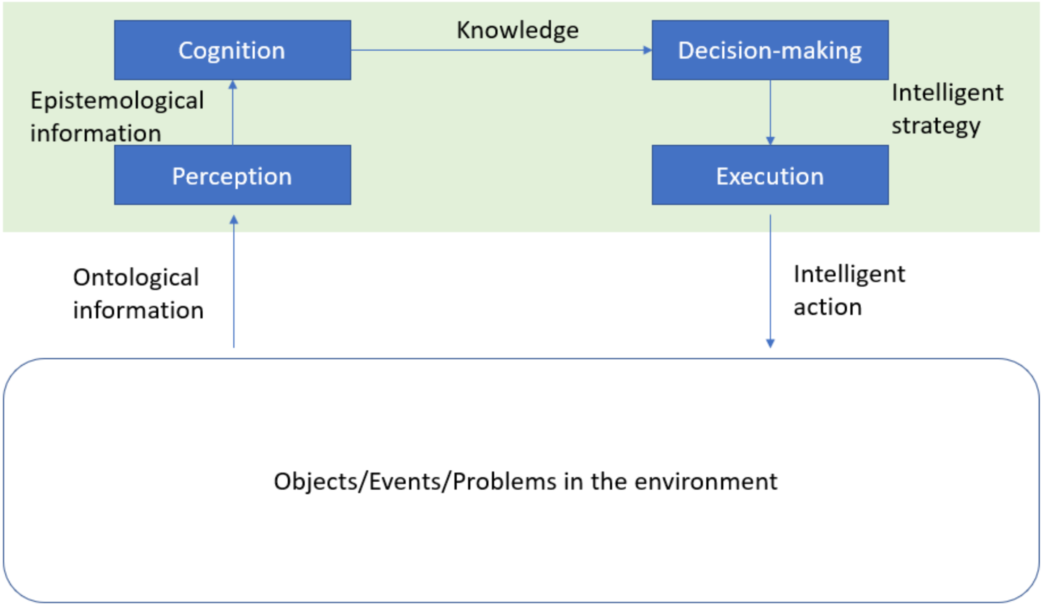

Figure 3 – An IoT-based AI functional model (ZTE, 2015)

Similar processes can be executed by several AI entities (autonomous algorithms, systems, devices and robots) within the urban space, that offer alternative smart services, which result to a complex system of systems. Talari et al. (2017) provide a pool of alternative IoT applications in SC, which complies with the ITU-T FG-SSC.0345 (2015) *Smart and Sustainable Cities Architecture* (ITU, 2015c), and which depicts service and information flows within the SC context (see Figure 5).

Taking into account the above AI functional model, the energy demand E_{AI} of the n existing AI systems within the urban space can be calculated with the following formula (9):

$$E_{AI} = \sum_{i=0}^{n} \int_0^T D_i(t)dt \tag{9}$$

where total energy demand E_{AI}, is obtained by integrating power demand (D) over a specified time interval T (Dersin and Levis, 1982) with peak times containing the maximum E values. However, some parameters influence this demand:

1) The amount (n) of the devices in the ecosystem where the AI applications run and which demand this amount of energy.
2) The amount (k) of requests/signals that submitted in the form of energy between devices that interconnect these AI applications/devices with the ecosystem.
3) The computational power or use phase energy consumption (E_u^{ω}) that each of the AI applications consumes during its operation, which depends on the operational time (t).
4) The amount of energy that the host device of each AI application (e.g., robot; autonomous vehicle; workstation; mobile device etc.) requires during its operational time (t). It can be calculated with the use of the p*ower usage effectiveness (PUE)* index (coming out from formula (5)), that is being used for computation power calculation (Bashrush, 2018):

$$PUE = \frac{Total\ facility\ load}{AIIT\ Load} \tag{10}$$

which indicates the facility energy consumption overhead (to cover cooling, power infrastructure, etc.) compared (divided) by the useful information technology (IT) load performed for the AI (AIIT).

5) The amount of energy (I) that the host device consumes during its idle time (idle).

Let us consider a workload ω, which runs over θ facilities, where each facility s_m has an average utilization of a_{sm} and active idle β_{sm} and 100 percent capacity power as P_i^{sm} and P_f^{sm}, respectively. The use phase energy consumption, E_u^{ω}, of workload ω can be calculated as follows (Bashrush, 2018):

$$E_u^{\omega} = \left(\sum_{m=1}^{\theta}(P_i^{sm} a_{sm} + P_f^{sm} \beta_{sm})\right) x \; 8.76 \; x \; PUE \tag{11}$$

In this regard, the total amount of energy that is being consumed in such an ecosystem, can be calculated with the following formula:

$$T_E = \sum_{i=0}^{n}(E_u^{\omega}) \tag{12}$$

On the other hand, AI is fed with huge amounts of data (big data), which makes possible the execution of the above process (Figure 3) and the overall process for big data used by an AI system (Figure 4) is analyzed as follows (Etaati, 2019):

1) **Understand business problem**: since not all issues can be addressed by AI, and use-cases are necessary for AI perception and recognition, business stakeholders, data scientists and engineers, work together to define the problem and determine the appropriate data sources and decision making process.
2) **Ingest data**: *collecting* required data from different resources, *exploring*, *cleaning and transforming* it.
3) **Modeling**: it concerns model selection after analysing the problem and data. Most data is allocated for model creation (training), with a small proportion to be used for model evaluation.
4) **Deployment**: it concerns the execution phase, where AI is triggered and the model is being evaluated and monitored.

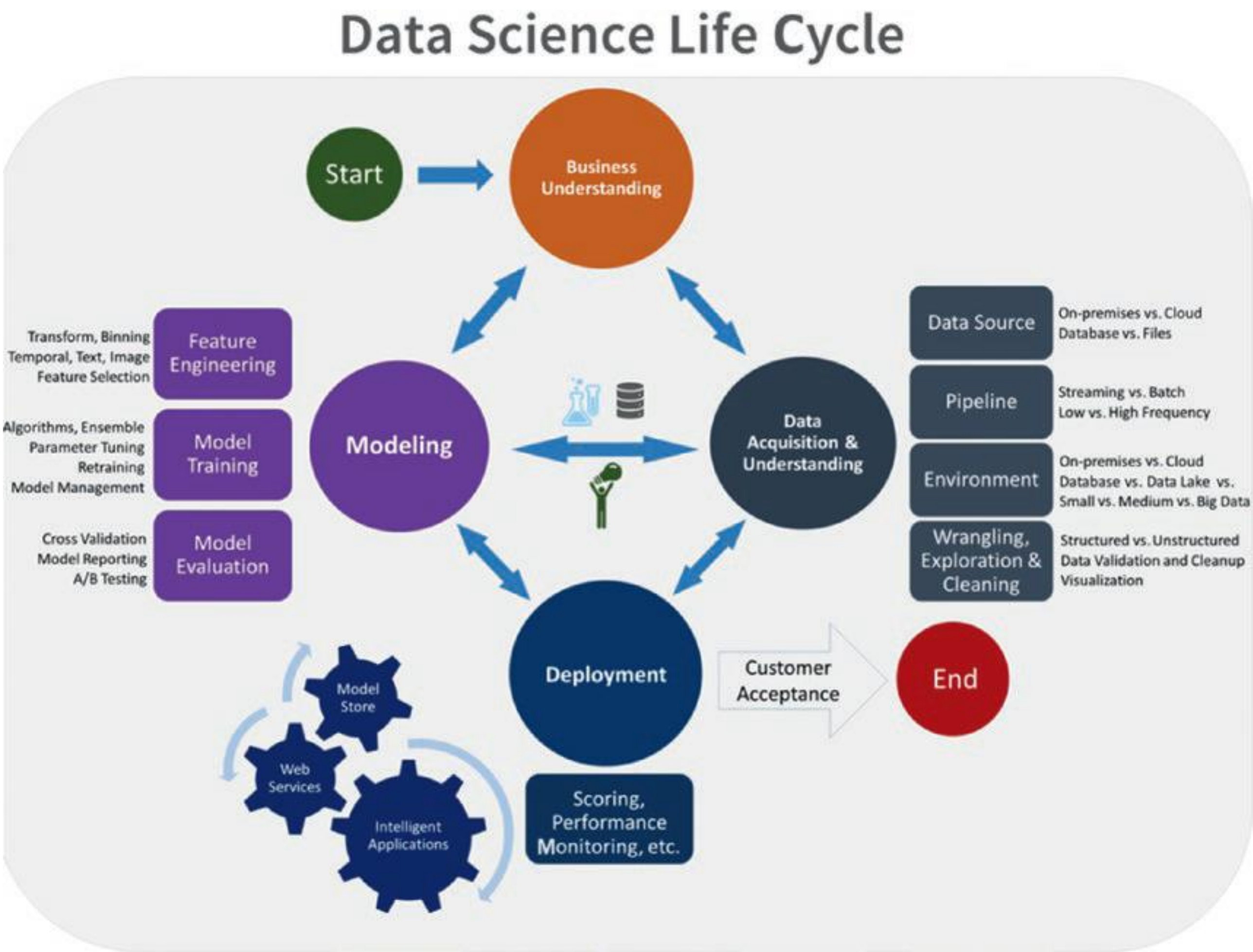

Figure 4 – Data science life-cycle (Etaati, 2019)

The above process shows that energy demands for big data concern only the following from the above process steps, which conclude to formula (13):

1) *Data collection* (by IoT). The IoT requirements can be seen in Recommendation ITU.T Y.4113 (2016) and they deal with several devices (sensors, actuators, cameras, etc.) and even mobile devices that are used for data collection.

2) *Data storage* (in sensors (low energy demands) and data storages, local (thus, the required data centres) and cloud-based (remote demands).

3) *Data transmission* (several network pipeline operations: IoT networks (low power local areas (LPLA) and low power wide areas (LPWA) such as the ones explained in (ETSI, 2015), xG networks, typical cable and fibre-optic networks, all with the corresponding gateways, and other network equipment).

4) *Data processing* (wrangling, exploration, cleaning).

$$E_{data} = \int_0^T DC_i(t)dt + \int_0^T DT_{IoT(i)}(t)dt + \int_0^T DT_{mobile(i)}(t)dt + \int_0^T DT_{cable(i)}(t)dt + \int_0^T DT_{dataCenters(i)}(t)dt + \int_0^T DT_{cloud(i)}(t)dt + \int_0^T DP_i(t)dt \quad (13)$$

where total energy demand *E*, is obtained by integrating power demand (*D*) over a specified time interval *T* and:

– *DC*: the energy amount that is consumed for IoT device operation for data collection, during the T time interval.

– *DT*: the energy amount that is consumed for network operation for data transmission, during the T time interval. This amount is analyzed in:

- DT_{IoT}: IoT network's operation demand for this transmission.
- DT_{mobile}: with the use of formula (4) or according to ITU L.1210 (2019c) and the use of the following formula (14) for the site energy efficiency (*SEE*) when speaking for specific geographic areas (site):

$$SEE = \frac{E_{CT}}{E_{TS}} \times 100\% \tag{14}$$

where *SEE* is the ratio between the total energy consumption of telecommunication equipment and the total energy consumption on site. A particular sum of energy is provided to one site where only part of the energy goes to main devices while the rest is consumed by site-supporting devices such as lighting, cooling, power supply units (PSUs) and power distribution.

- DT_{cable}: power usage for the cable network's operation for these transactions.
- $DT_{dataCenters}$: it can be calculated according to ITU-T L.1302 (2015).
- DT_{cloud}: transactions with clouds that the system requests.

– *DP*: the energy amount that is consumed for facility's operation during data processing, during the T time interval. This amount can calculated with formulas (11) and (12) too.

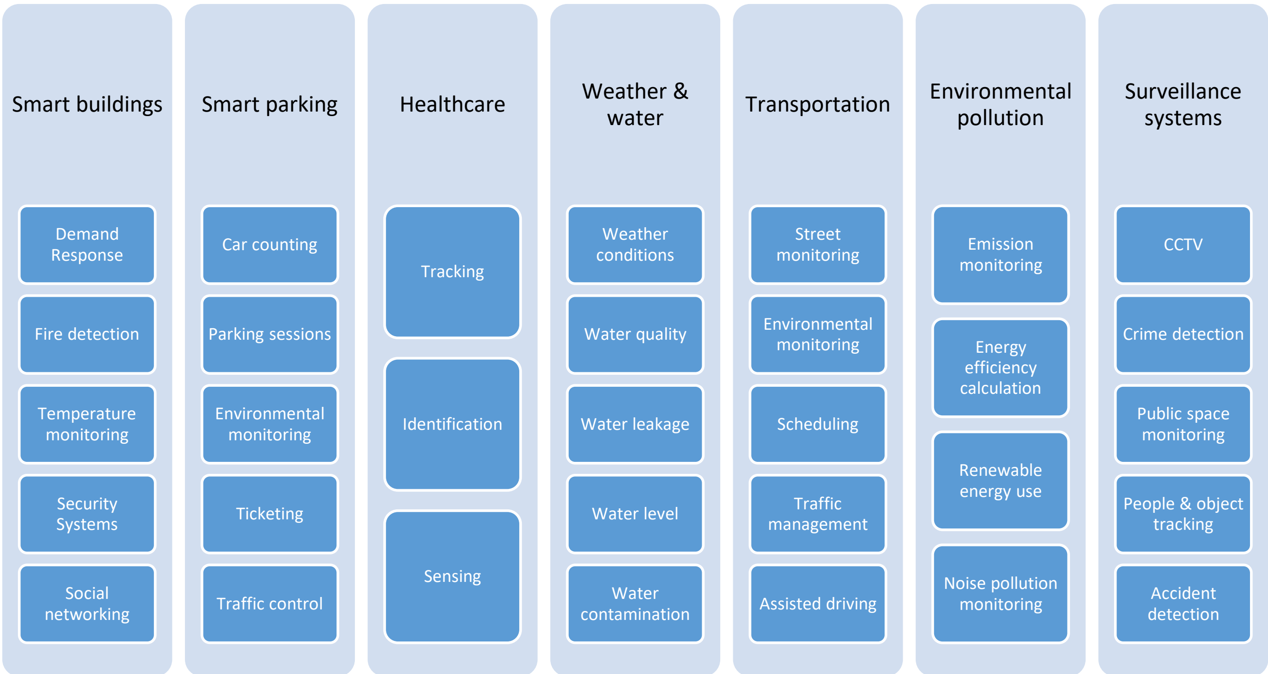

Figure 5 – IoT applications in smart cities (Talari et al., 2017)

5 Research methodology

The models referenced above indicate how energy efficiency is approached in cities but, they do not focus on specific emerging technologies or systems that use AI and big data. In this regard, the methodology approach followed in this work includes a detailed and systematic review on pertinent literature, mostly focusing on recent studies that explore energy efficiency metrics and models, as well as the impact that the specified technologies (AI and big data) may have on urban energy system performance.

A search on scientific repositories with the combination of the appropriate terms/keywords such as *"city" AND "energy efficiency" AND "assessment" AND "model"* returned numerous articles that had to be explored. In ScienceDirect[3] alone, more than 14,000 articles were retrieved with this search in March 2020, some of which are reviews of existing assessment models (1,560). Such a size and spread of results, questions the number of available models and their potential. The incorporation of *"AI"* as an extra keyword decreased this number of results to *594*, while *90* records were generated with the extra keyword of "big data" (the inclusion of *"big data"* instead of *"AI"* returned more than 612 records). From the 90 records that were collected from this repository, the authors performed a first screening on their title and abstract, to identify their relevance with this study and kept 54 articles. From these records, 43 were studied further after a second screening, which attempted to keep only the works that review energy efficiency systems within cities, under the lens of AI, big data or both. A similar process was followed in the rest of the examined scientific repositories, while articles located in more than one resource was counted once during screening.

The first findings from the collected articles (listed in Table 2) showed that most of them focus on the energy behaviour of buildings, which sounds reasonable since buildings represent almost the 80% of the urban energy demand system (Anthopoulos and Giannakidis, 2017). Additionally, many of the collected articles focus on operational systems (transportation and supply-chain). The methodology of this work relies on appreciating the existing methods for assessing the energy efficiency in an urban system, while at the same time identifying gaps between what has so far been found and what is potentially considered promising, yet challenging in the new technologies implementation phase. This study results to a taxonomy for urban energy efficiency assessment. This taxonomy can be used by policy makers to understand the domains whose energy performance is affected by AI and big data (i.e., buildings, mobility, etc.) and the methodology, the parameters or the alternative energy efficiency assessment models that are being used by these domains, according to the literature review.

Table 2 – Analysis of collected articles

Source	Review articles	Research articles	After screening
ScienceDirect	19	35	43
Scopus		3	2
Google Scholar	97	2,320	7

5.1 General reviews

A detailed presentation of the state-of-the art, energy-smart technologies that have been developed and implemented or are being developed throughout the world is given in Lindfield and Steinberg (2012). Furthermore, in a recent work by Abbasabadi and Ashayeri (2019) proposed a framework that aims to overcome the uncertainty limitations associated with the oversimplifications assumed in simulation methods and the use of aggregate data in data-informed approaches. A general compilation of methodologies, approaches and tools in renewable energy and energy efficiency projects' and policies' assessment was performed by Duffy et al. (2015).

The use of reinforcement learning (RL) techniques based on multi objective ant colony optimization (MOACO) algorithms for optimal dynamic resource allocation via a mobile edge computing approach was proposed by Vimal et al. (2020) within the industrial Internet of things (IIoT) framework.

[3] www.sciencedirect.com.

A structured literature review and detailed analysis study on Smart Energy City (SEC) projects featuring sustainability objectives was performed by Hunter et al. (2018). Sellak et al. (2017) provided a comprehensive analysis of the up-to-date research in the field of energy planning decision-making (EPDM).

A critique on the IT revolution and its impact on human involvement and cultural aspects was presented in a study elaborated as a sequence of research work aiming to suggest an alternative perspective for developing strategies to design and implement systems that work better for the society (Slaughter, 2018). This work discusses issues related to IT implementation with respect to societal gains through two distinct case studies; one on the IoT and the other on the Autonomous Vehicles (AVs) case.

Reflecting on the plethora and impact of recent research endeavours addressing computationally complex problems by using bio-inspired models, Del Ser et al. (2019) identified the state of the art research advances and promising challenges in a diverse range of areas in which bio-mimetic models are applied, including the energy domain. Regarding energy efficiency assessment applications, some algorithms respect the environmental sustainability goal, whereas adequate alterations in algorithmic design aspects (i.e., resource allocation, memory indexing and processing time etc.) need to be accounted for. In addition, it is indicated that green computing can be effectively applied as an alternative tool at the early stage of the algorithm design process.

5.2 Buildings and blocks

A structured literature survey on intelligent energy management systems applied in buildings was also performed by de Paola et al. (2014), focusing mostly on the available architectures and methodologies followed within the framework of a smart home vision. This work highlights the importance of precisely defining configuration procedures to reduce human intervention and enable a user-friendly interface. It also suggests an automatically perceived energy consumption model that can directly utilize the obtained measurements and points out that a support mechanism for the final user of the energy monitoring system has not been developed yet. Quite similarly, Vahid et al. (2016) modeled the energy retrofitting measures for residential stocks with the use of data from smart buildings, while Li et al. (2017) modeled the building energy demand with big data analytics.

Through a Life Cycle Analysis (LCA) perspective and stakeholders' point of view, the problem of building energy performance was reviewed in Zou et al (2018) and Heeren et al. (2013). The first study pinpointed the so-called 'building energy performance gap' (BEPG), which constitutes the gap between the actual energy consumption in buildings and the predicted or simulated one, outlining significantly big discrepancy characterized also by the large number of research studies performed over the last decade. The second study modeled new building stocks with a 3-entity process (input, calculation and output) and evaluates the energy performance of buildings with annual space heating demands and thermal quality, distinguishing new, from renovated and old blocks.

In an effort to classify and assess the large number and diversity of the existing approaches that aim to model energy building consumption and efficiency, a critical review work was conducted by Koulamas et al. (2018). A hybrid framework is suggested to be implemented in order to provide the best possible solutions, by utilizing bill-based approaches to derive the initial dynamic models that can, in turn, be optimized by measurement-based methods.

Jia et al. (2019) identified technical requirements of an integrated IoT capable of serving the contemporary needs of the building industry and indicate the main challenges for advanced smart buildings development through improvement of the current technologies maturity in terms of hardware, software and computing algorithms.

Geraldi and Ghisi (2020) performed a literature review on the energy performance of buildings and introduced the concept of zero energy building (ZEB) to decarbonize the existent building stock. Recognizing the importance and challenges in energy monitoring, the authors suggest that technological advances in sensors and energy meters that can be implemented in smart buildings could largely benefit energy management in the building sector.

Within a building scale applications context, a review of studies on energy consumption modelling and forecasting has also been recently conducted (Bourdeau et al, 2019). This work offers an outlook on the latest technical advances and research efforts that prevail in modelling and forecasting buildings energy consumption, while emphasis is given in data input characterization and pre-processing methods illustrated in the literature. Data-driven approaches are discussed and their capability of being adapted to various situations related to key aspects is underlined. These main problem-specific aspects that need to be considered are the particular end-uses of energy, the forecasting horizons and accuracy, as well as the building typologies and the key role of occupants' involvement in data-driven energy consumption modelling. However, it is pointed out that although these methods are widely applicable, a unified protocol that can address the variety of pertinent issues within an integrated smart infrastructure context has not been developed yet. Particular attention is also given to the implementation of different machine learning techniques in energy use modelling and forecasting approaches.

Building performance analysis was the focus of a paper that addresses the complexities and recent challenges in the field (de Wilde, 2019). Energy efficiency is one of the key dimensions in estimating building performance. Ten research questions were addressed based on the existing body of knowledge, most of them emphasizing the different perspectives from which performance analysis of buildings is examined. From an engineering point of view, user needs translated as technical performance requirements, are compared with the observed and quantified behaviour of a building, whereas special constraints for each structure calls for a more tailor-made approach. Furthermore, this study estimates that there are more than 60,000 papers that address this topic and are spread over a large number of journals. Main research contributions are also pointed out in this work, providing a basis upon which new research directions can be considered for the effective design, construction and operation of buildings that can fulfil the expectations of all stakeholders in this sector.

Energy efficiency optimization based on users' behaviour was a central theme in a research study conducted to demonstrate how appropriate digitalization systems can provide optimal solutions (of low cost and high performance) to building energy management problems (Habibi, 2017). Smart sensor systems and digital simulation tools are suggested to be employed for real-time data acquisition in intelligent building energy management systems. The study suggests that in order to tackle climate change issues associated with building energy utilization, employing AI and neuroscience in the context of machine learning approaches, can play a pivotal role in the improvement of energy efficiency in an urban environment.

The problem of managing a complex exhibition system in which interactions of both physical and intangible elements occur, was addressed by Uva et al. (2017). A modelling framework for a sustainable co-management scheme was developed and its utility was demonstrated through a case study in which a complex (multi-variate and multi-scale) exhibition district (the Fiera del Levante or FdL) was considered. Through the framework developed in this work, a methodology for an integrated assessment of seismic and energy vulnerability at the urban scale was proposed. Two indices, namely the seismic vulnerability index (IVS) and the energy vulnerability index (IVE), were introduced with respect to a particular building and calculated through the described procedures. The study emphasizes the concept of big data to enable the analysis of a big data load and the utility of biomimetic models to support sustainability analysis.

Biomas gasification-based combined cooling, heat and power (CCHP) systems applied in two types of Singapore's buildings (i.e., data centre and commercial building) were analysed on the basis of process performance evaluation in terms of energy efficiency, economic and environmental perspectives (Li et al., 2019). The study evaluated different biomass feedstock and performed sensitivity analysis with respect to resources cost. Research results showed that the overall performance of the commercial building case was higher than for the data centre due to the increase in the primary energy ratio attributed to the enhanced electrical power efficiency, as well as to more favourable cooling to cooling ratios.

An insightful review on the utility of combining big data (BD) techniques with AI methods for achieving energy efficient building designs was presented in Mehmood et al. (2019). This study describes the evolvement of AI, outlines the advantages of embedding BD to AI methods for sustainable building design and operation, and provides an overview of recent applications of BD and AI to enhance energy efficiency in buildings, highlighting the perspectives of new approaches in machine learning and large databases. Large datasets that deal with buildings and can be utilized by analytics and AI are the following (Gilani et al., 2020): external conditions; indoor conditions; building systems/components; energy use; maintenance; occupant-related data; physical building information; performance-based data; and simulated-based data.

5.3 Utilities and other sectors

The development of a more technically-oriented ecosystem service framework based on the IoT and cloud concepts within a particular smart cities' project in Italy was carried out by Bruneo et al. (2019). This research work demonstrates the utility of flexible, low-cost and adaptable strategies for smart services in small and medium size cities. Such approaches refer to reuse, resource virtualization, multiplexing, and software-defined cities that can be applied on an existing and shared testbed infrastructure that enables the simultaneous implementation of several efficient (smart) urban services, such as smart mobility, smart environmental management, as well as smart energy and lighting. A quite alternative approach (Stewart et al., 2018) integrates the city utilities with networks and data flows and create opportunities for multi-utility service provision, as well as for new business models (e.g., energy consumption analytics; sensor-based metering, etc.) (Schweiger et al., 2020; Yohanandhan et al., 2020; Mbungu et al., 2019).

Another study on integrating data sets for domestic energy reductions in cities proposed a novel spatially-based framework for modelling energy consumption in sub-city areas in the UK, on three different aggregated scales: district, neighbourhood and communities (Urquizo et al., 2018). Energy profiles for dwellings were estimated, and then a cluster model (top-down approach) and a sub-city domestic energy model (DEM) (bottom-up approach) were generated and utilized depending on the outcome scale. The study uses a multi-source data set and a heat balance model to assess the energy consumption at a dwelling level and can provide insightful energy efficiency analyses to inform various implementation strategies and integration opportunities for renewable energy sources into the overall generation portfolio.

Chen et al. (2019) explored sustainability issues in overall utilization efficiency of urban infrastructure across cities in China. Data inputs of an urban infrastructure system considered in the Super-slack-based utilization measure model were road, water, communication, education, healthcare, environmental sanitation metrics, along with energy utilization data. Moreover, the dynamic behavior of the utilization efficiency among a sample of cities was further examined using the Malmquist productivity index (MPI). The study highlights the importance of improving utilization efficiency of cities' infrastructure by employing advanced digital technologies and implementation of effective tools, such as big data, cloud computing and Internet of things that enable a better utilization assessment leading to a more sustainable urban development.

An extensive review work on information integration in various industrial sectors was carried out by Chen (2016). In this work, trends in ICT integration in the energy sector - among other sectors - were also discussed. In particular, three distinct studies that deal with energy efficiency issues were identified in this work; Fleiter, et al. (2011) reviewed energy efficient technologies targeting industrial energy demand from a model's limitations point of view; Hackl & Harry (2014) proposed an integrated heat recovery model based on total site analysis (TSA) aiming at enhancing energy efficiency, whereas Blomqvist and Thollander (2015) developed an energy efficiency metrics framework that accommodate integration of relevant data from two countries (namely Sweden and USA).

Along the same lines, Flick et al. (2018) discussed the challenging issue of energy transparency implementation in the industrial sector through application of the big data concept conforming to the ISO 50001 principles. In particular, the utilization of the internal energy-related data of industrial process equipment as part of an industrial big data (IBD) establishment is the focus of this research. A classification assessment framework for energy-related data acquisition by employing the IBD infrastructure (enabling use of data extraction, processing and storage methods and tools), along with machine-embedded data available in a process, without having to use any external measuring devices, is here proposed for a reliable and cost-efficient energy management approach. This approach has only applied for the case of electric energy, but need to extended to various energy forms in industrial process applications at a larger scale. In addition, it is necessary for the proposed framework to become capable of handling a big load of data processing, as demand is continuously increasing, and providing further characterization within data (e.g., on peculiarities, abnormalities etc.) in a more holistic assessment framework.

In the context of Industry 4.0, Zhong et al. (2017) conducted a review study on topics related to intelligent manufacturing and smart production systems enabled though the IoT and cloud concepts. Comparisons among such systems were also provided. Technological advancements on cyber-physical systems (CPSs), big data analytics, ICT and cloud computing that can facilitate intelligent manufacturing transformation were discussed. Strategic planning performed by governmental bodies and international firms, for realizing Industry 4.0 through developments in such systems were highlighted, whereas major challenges and future perspectives were also outlined. Among other findings, the study stated that the IoT enabled improved energy efficiency and integrated energy management in smart city's projects realized in Italy and Spain.

A bibliometric analysis on articles considering environmentally conscious/responsible, sustainable, green manufacturing systems was carried out by Pang and Zhang (2019). Furthermore, an eco-socio-economic classification framework for research in the field of green manufacturing, with respect to three levels of assessment, namely application, organization and systems-based, was created. According to this study, the most dominant dimension in green manufacturing literature, as indicated by the frequency of keywords used, is shown to be energy consumption and efficiency. Several findings reveal trends in recent sustainability research, one of which considers energy management of paramount importance in green manufacturing strategy. In addition, the study emphasizes the impact of new technologies, such as AI, 3D printing, big data, etc. in green manufacturing systems at all levels of potential implementation. It was also pointed out that although energy issues are extensively considered at the systems- and organizational levels, practical applications of green energy have not received much attention yet and more applied research is needed in this area.

Kumar and Anbanandan (2020) developed an environmental and social sustainability (EnSoS) assessment framework, especially for freight transportation systems, by employing an integrated multi-criteria decision-making (MCDM) approach, the fuzzy best-worst method. The proposed framework assesses the sustainability performance of a freight transportation system using a fuzzy performance index and identifies the obstacles to the sustainability of such a system. Energy efficiency in logistics operations has been identified as one of the main attributes evaluated through the EnSoS framework to be considered in the development of a sustainable transportation policy.

Another recent review work focusing on studies applying artificial intelligence (AI) methods to address problems in the architecture, engineering and construction (AEC) industry was conducted by Darko et al. (2020). This study was an extension of an earlier work carried out by the same research group dealing with an inclusive scientometric review of Global Green Building Research (GGBR) (Darko et al. 2019). The research aimed to identify collaborative networks of certain research interest in the particular sector and reveal gaps in future research directions. The review showed that energy, as a potential research topics among other topics, addressed by AI applications in AEC, has not received much attention in relevant literature and suggested that R&D efforts need to focus on how to integrate AI methods in energy and other sectors.

The implementation of the smart city concept with respect to sustainable transportation, especially in response to transport-related CO2 emissions reduction is considered in a research study carried out by Zawieska and Pieriegud (2018). CO2 emissions generated from Warsaw's transportation system are estimated for different application scenarios by employing the United Nations' ForFITS (for Future Inland Transport Systems) model. However, several assumptions have been made in applying this model for future forecasts and projections regarding the greenhouse gas (GHG) emissions estimation; such assumptions refer to the economic indicators of a region (e.g., GDP per capita) considered constant, uncertainties related to technological progress that is overlooked (energy efficiency enhancement, changes in emission factors etc), and more. Other uncertainty sources in the model include future demand for new technologies, fuels and services, as well as pertinent changes in the automotive industry. The study highlights the challenges that need to be addressed in order to achieve an effective transformation of the transportation and energy sectors, and confirms that smart city tools can help in mitigating transport emissions and meeting reduction targets.

A more generic and practical approach to urban management was considered through the invention of an innovative monitoring device for micro-climate and air pollution assessment in an urban setting (referred to as uCM) that was developed in the form of a conveniently portable backpack providing real-time information to all interested parties in an open data structure (Gallinelli et al, 2017). The hardware and software development of the uCM is an ongoing process aiming to contribute to better informed urban management efforts with various applications, such as in traffic control, pollution prediction, health assessment, green city's design and planning, etc.

A digital multi-utility service system is proposed by a research study that addresses the specific transformative process and features of the system, such as its architecture, along with the advantages, challenges and possible implementation strategies (Stewart et al., 2018). The study emphasizes the integration opportunities of a digital service provider that is capable of employing data modelling processes and informatics. The concept is illustrated through several examples and water-energy nexus case studies in which proper data metering systems and informatics are applied. The paper also suggests R&D priorities to be considered for facilitating the realization of the digital multi-utility transformation envisioned in this work.

Along similar lines, a holonic systems approach was proposed by Tokody (2018) for digitalizing the European industry. Smartness metrics was also defined based on identifying smartness indicators in cyber-physical systems and at different levels based on the 5G architecture classification. The study argues that by developing an appropriate holonic means, a generic cyber-physical system (CPS) giving rise to a smart factory can be further achieved. It is also concluded that such intelligent systems can significantly contribute to improving sustainability, flexibility and efficiency in manufacturing systems.

The digitalization in the agricultural industry for a sustainable bio-economy under the umbrella of environment-food-energy-water nexus considerations as a whole was also discussed in Ghani et al. (2019). The technological readiness level for assessing the biomass availability potential with respect to such a nexus interface was analysed, pointing out that high computational requirements for processing huge data sets in a software need to be taken into serious consideration in order to inform sustainable and often competing resource management policies in Malaysia with an outlook for other countries' similar agricultural practices. It was concluded that AI and contemporary ICT practices can significantly contribute to a smart agricultural development serving well-balanced sustainability objectives. To this end, precision wireless network enablers, robotics for automated crop survey, global positioning systems, drones, smart farming equipment and IoT are some of the examples that can contribute to accelerating the future of agriculture, without compromising on natural resources overutilization practices. The study suggests that scaling up smart agricultural methods and bringing together policy makers to develop practical implementation policies are major challenges in agricultural transformation.

In the field of healthcare management, Turjman et al. (2020) conducted a literature review on the Internet of medical things (IoMT) and its interdisciplinary aspects and applications that enable the exchange of healthcare data leading to better healthcare services and more cost-effective systems. This work focuses on the summarizing the current status of the IoMT, but also pinpoints technical and design challenges encountered in this field. It also identifies four pillars within an IoMT framework proposed to overcome these challenges; namely data acquisition, communication gateways, and servers/cloud components. The paper also illustrates the perspectives of the IoMT eco-system in practice and argues that new technologies are still needed for improved healthcare systems. For instance, it was mentioned that advanced technical solutions are necessary to reduce energy consumption that occurs as a result of the large volume of data generated. Although sensory technologies reduce healthcare cost and improve services, they still need to be more energy-efficient and technically robust to contribute in developing better healthcare information systems. Energy harvesting modules are suggested as an alternative to convert various energy forms into electrical energy. Furthermore, the research regards WANs as reliable network infrastructures, but points out that they still exhibit high power consumption. Finally, is was indicated that although data mining is a very efficient tool in healthcare services, it is not capable of performing adequately for all types of datasets; thus, perhaps a hybrid approach in data management is needed for associating different classification models within a proper decision support system.

The problem of modelling and traceability for precision engineering and metrology, especially when intensive computational needs in complex engineering systems are highly required, was addressed by Linares et al. (2018). In this work various issues regarding the stability and conditioning of computations, as well as metrology and precision engineering software suitability are considered and continued research efforts are suggested to be made in order to further improve these components in the implementation phase, thus leading to models that become capable of performing high-precision calculations. These models can be of significant value for assessing energy efficiency and rigorously managing energy utilization within complex systems.

In a recent review work on tourism demand forecasting, scenario-based research studies regarding energy consumption, climate change and sustainability in an attempt to forecast the tourism environment were pinpointed (Song et al, 2019). Two scenarios were considered in one of these studies, providing an outlook to possible future energy consumption and environmental pollution options based on economic assumptions (Yeoman et al., 2007). The second research study employed 70 scenarios focusing mainly on energy efficiency improvements via incorporation of all possible strategies and technologies and 4 automated backcasting scenarios. Moreover, Stahan (2014) attempted to define an energy-efficient architecture for sustainable urban tourism, which focuses mainly on green hotels. Numerous organizations perform the assessment of energy-efficiency (i.e., Green Leaf, Green Seal, Green Key and Eco-label, Green Tourism Business Scheme [GTBS], China's Green Hotel Standard [CGHS], LEED and BREEAM etc.). The energy efficiency assessment was based on the most frequently used evaluation models, which are analyzed in three main dimensions that deal with sustainable development: the ecological, sociological and economic dimension. The ecological dimension is analysed further in environmental protection, protection of nature and characteristics of a building.

5.4 Trends in energy efficiency

As was presented earlier, the examined articles did not address how the emerging technologies affect the performance of urban energy system, but only a few articles consider estimating the energy demands: of 5G (Barakabitze et al., 2020; Li et al., 2018); of precise agriculture (Vuran et al., 2018); and of the mass transportation of passengers that use technologies during their trips (Noussan and Tagliapietra, 2020).

Moreover, within a different research scope in energy efficiency optimization, Baker et al. (2015) addressed the problem of rigorously determining the most energy efficient path in a cloud network environment, in which big data need to be processed and stored. The research efforts were centred around the development of a new routing algorithm to account for the continuously increasing demand of data transferring between data centres and users, resulting in an efficient and sustainable cloud networking framework.

AI, machine learning (ML) and deep reinforcement learning (DRL) techniques aiming at enabling smart cities evolution and policy making were discussed in a review paper by Ullah et al. (2020). The study offers many details on their applications in intelligent transportation systems, cyber-security, energy efficiency of smart grids, smart healthcare systems, blockchain and effective use of unmanned aerial vehicles (UAV) through the optimal use of 5G and beyond 5G (B5G) communications. It also focuses on several research challenges encountered in complex systems for realizing the concept of smart cities in the future. With respect to energy efficiency, it was pointed out that big data analytics can significantly impact energy management and consumption in smart grid operations, whereas ML and DRL techniques can be employed to optimize UAV's energy consumption and efficiency in intelligent transportation systems. In addition, the paper cites another study on cyber security that proposes a computational offloading framework in a Fog-Cloud-IoT environment based on an ML model to optimize energy consumption and ensures data security. Several AI-based models can be located to be applicable in energy consumption forecasting (i.e., ANN, SVR and random forest (RF) (Wei et al., 2019).

In SC the role of the ICT in energy has been labelled "smart energy" and deals with the embeddedness of smart infrastructure and services in energy provision and consumption (Anthopoulos, 2017; Abdurahman and Patel, 2019). An interdependence between power provision networks that incorporate intelligence for improving their performance (smart grids and smart microgrids) and the consumers (e.g., buildings, transportation networks, electric vehicles, lighting, electrified highways and appliances etc.) can be seen in the SC ecosystem (Amini et al., 2019; Yohanandhan et al., 2020; Mbungu et al., 2019).

5.5 Towards an energy efficiency taxonomy for AI and big data

The above literature evidence provides a primary taxonomy onhow energy efficiency assessment is being approached from the perspectives of AI and big data, especially within cities (see Figure 6). This taxonomy shows that energy efficiency in SC is seen within *sectors/domains* of the overall ecosystem, while alternative smart technologies are being used to calculate and enhance this energy efficiency. The primary sectors/domains concern (a) buildings; (b) utilities and other sectors; (e) emerging technologies. Within each *sector*, AI and big data play different roles (i.e., for enhancing heating/cooling, operational analysis and maintenance estimation), which can be called *sub-domains* or *uses* and in this regard, energy efficiency has to be calculated accordingly. Literature findings demonstrated how energy efficiency is considered in each sub-domain/use (i.e., energy performance gap estimation for heating/cooling of a system, with the use of AI and big data). In this regard, this taxonomy details *roadmaps* for energy efficiency assessment.

The assessment model that can be used for energy efficiency cannot be a unified one, and policy makers have to follow the appropriate roadmap according to the particular domain and sub-domain where they focus. Nevertheless, the background findings that explained the AI and the big data processes, resulted to formulas (12) and (13) accordingly, which can be aligned to any of the particular purposes of this taxonomy and in this respect, they can be considered to be appropriate for the purposes of this document. In case the city holds the necessary data, these formulas can estimate energy demands for policy makers to think of means that enhance energy efficiency (increase the outcome; minimize the energy demands; or both).

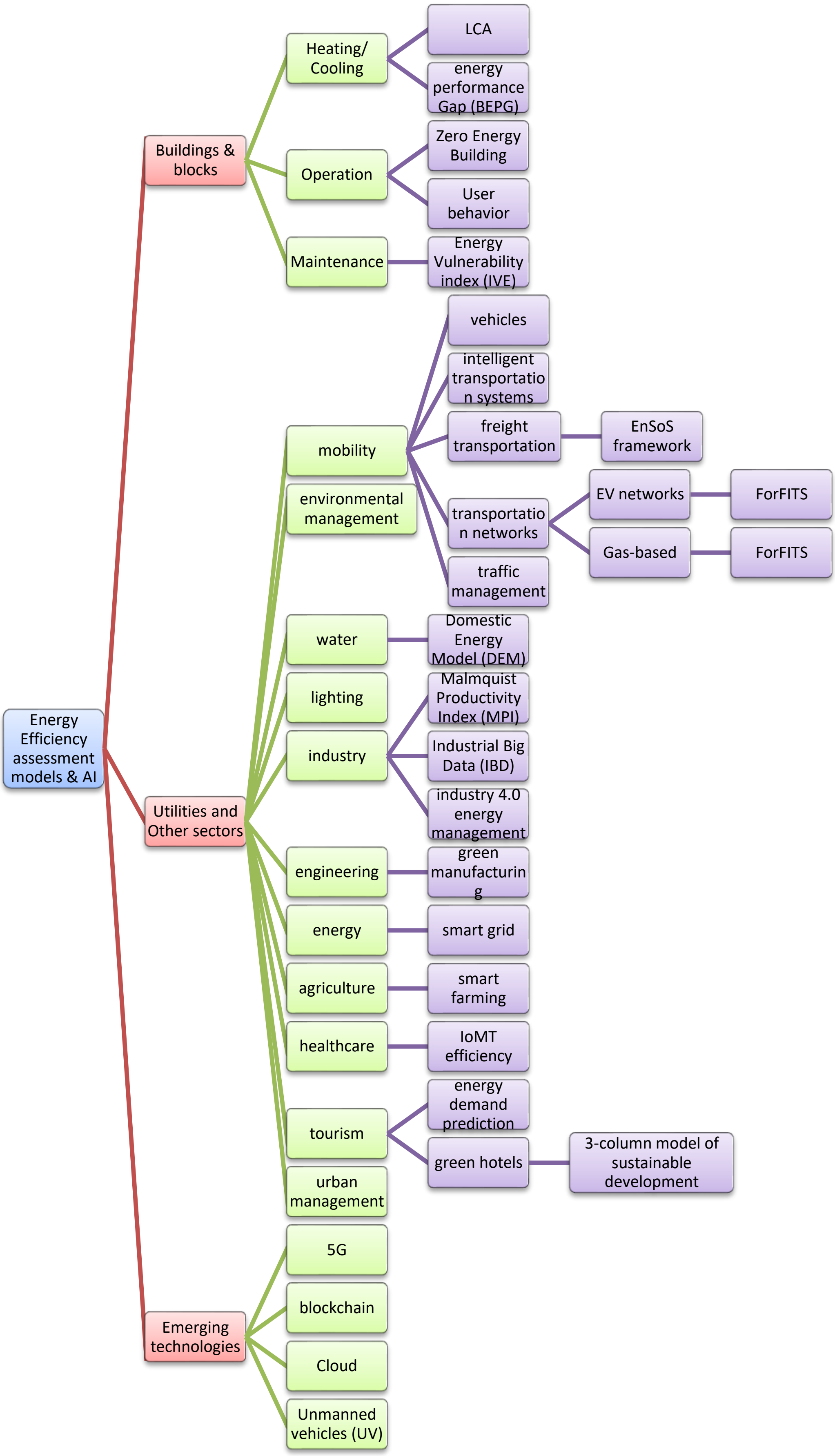

Figure 6 – Taxonomy for urban energy efficiency assessment, from AI and big data perspectives

6 Conclusions

This document attempts to detail how energy efficiency can be assessed within the urban space, under the lens of AI and big data. It began with the observation that both these technologies emerge within cities, with a promise to enhance urban operation, improve urban life and achieve in economic growth. Nevertheless, the adoption of these emerging technologies result in increasing energy demands and corresponding environmental footprint, which question their potential.

Thus, the aim of is document is two-fold:

a) Analyse the background of energy efficiency assessment, AI and big data, to estimate the corresponding energy demand sources and size, and to conclude to models that can perform an energy efficiency assessment within the urban space, using both AI and big data.

b) Define a taxonomy for energy efficiency assessment in the urban space, under the lens of AI and big data. This taxonomy can help policy makers to understand what to measure, in which sector and how, and to design policy measures that enhance corresponding energy efficiency.

For the purpose of this document, several standardization documents, scientific books and articles and mathematic formulas were explored and extracted, with reference to technologies, which can perform energy efficiency assessment. The final recommendation is the following: the final outcome (i.e., service improvement; new product development etc.) that is generated by AI and big data has to be enhanced; the amount of the consumed energy has to be decreased; or both.

With regard to the first (a) aim of this document, formulas (12) and (13) can be considered unified to assess the energy efficiency of AI and big data. Additionally, (Figure 6) depicts the extracted taxonomy, with alternative energy efficiency approaches that are followed in sub-domains of the urban space, where the literature is focused. This taxonomy also considers competitive frameworks that can help energy efficiency assessment or the appropriate calibration of formulas (12) and (13).

Some future thoughts of this document will be to apply the model in real environments (e.g., in cities where specific AI and big data -related projects are launched, such as drone applications, autonomous vehicles etc.) where specific values can be collected and calculated. Some other future thoughts concern the investigation of the relationship of AI and big data energy efficiency with the circular economy and more specifically the corresponding consideration of circular economy's principles. Indicatively, in the case of buildings, these principles are -among others- the following:

1) The preservation and improvement of natural capital by controlling finite stocks, using renewable resources, where products, their components and materials have the longest possible lifetime, via the use of technical and biological cycles.

2) Resource optimization use, where manufacturing, restoration and recycling can be repeated in such a way that they recirculate.

3) Promote the efficiency of the building system, eliminating negative externalities.

7 References

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Appendix I

Representative Projects that focus on Energy Efficiency AI and Big Data

Introduction

ITEA[4] is Eureka's R & D & I Cluster program for software innovation, which enables a large international community to collaborate on funded projects that turn innovative ideas into new business, employment, economic growth and benefits for society. The ITEA program covers a wide range of business opportunities facilitated by digitization such as smart mobility, healthcare, smart cities and energy, manufacturing, engineering, and security and protection. ITEA drives important technology fields such as artificial intelligence, big data, simulation, and high-performance computing in specific business applications.

ITEA's vision in a rapidly changing society, digitization, is no longer just an option, but sees technology as an opportunity to create innovative solutions in all areas of society's activity. ITEA's main focus is innovative software development to drive that digital transition.

ITEA's mission is for companies to create innovative solutions with the participation of their clients in this digital process that address the main challenges facing society. To this end, ITEA encourages its global community to generate impact and value through R&D projects in the Software Innovation area through national and industry funding capacity.

Some projects that are being developed within the ITEA program related to AI and Big Data in the field of energy efficiency are listed below. These projects show the broad scope of AI and big data application in the energy sector.

AIDEMAS[5]: AI-enabled demand-side management for energy sustainability

Renewable electricity grids are affected by increased demand for high-power charging and the volatility of renewable sources. Demand-side management (DSM) is a framework that addresses this challenge through information sharing, integrated planning, and smarter decision-making across the network. However, a DSM implementation suffers from standardization, security, and data integration issues. The goal of AIDEMS is to power DSM platforms with new data models and machine learning algorithms that balance the search for optimal solutions that represent a greater part of the network.

AISSI[6]: Integrated stand-alone programming for the semiconductor industry

Digitization is driving increased demand for microchips and shortening the product life cycle, and the wide variety of customer-specific devices leads to a growing need for high-volume, low-volume (HMLV) semiconductor production. The AISSI (Integrated Autonomous Programming for the Semiconductor Industry) project proposes to obtain and develop, integrate and apply novel approaches based on artificial intelligence. By applying reinforcement learning and knowledge graphs in a continuous improvement framework for autonomous and integrated production and maintenance scheduling, the competition can outperform in terms of efficiency, cost effectiveness, and quality.

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4 https://itea3.org/about-itea.html.

5 https://itea3.org/project/aidems.html.

6 https://itea3.org/project/aissi.html.

AI4PV[7]: Artificial intelligence for the operation and maintenance of photovoltaic plants

The Paris Agreement has defined targets to limit global warming to 1.5° with a massive contribution from renewable energy. The industry has been working to improve the performance of photovoltaic (PV) systems, but unresolved challenges remain in terms of reliability and robustness, making tight integration into the electrical system difficult. In this context, the main objectives of the AI4PV project are to reduce the LCOE[8]) and increase the operational performance of photovoltaic plants through a hybrid use of physical models, AI and digital twins.

EFFECTIVE[9]: Energy efficient heterogeneous artificial intelligence platform for smart mobile and embedded systems

Basically, all mobile apps are heavily power limited, blocking large business cases. The increasing functional complexity in mobile and autonomous applications impacts the computational load by increasing the power demands of the integrated platforms, making them comparable to the actuation power demands. Today, it is generally recognized that "More AI requires less power consumption."

The EFICAS platform aims for significant improvements in the energy efficiency of AI solutions, enabling their diffusion into embedded systems in the mobility, communication and automation industries. EFICAS develops a holistic AI-powered software platform that merges and utilizes heterogeneous technologies by introducing runtime energy-sensitive cognitive middleware that utilizes performance and consumption markers from various computing technologies.

DEFAINE[10]: AI-Based Design Exploration Framework for Direct Loaded Engineering

To accelerate the commissioning of novel solutions and remain competitive, European players are forced to explore new product development approaches that can dramatically reduce delivery time. DEFAINE will deliver an advanced design exploration framework capable of reducing recurring costs in aircraft and wind power system design by 10% and reducing lead times for design updates by 50%. The framework will allow the design of improved solutions in the early stages of a project, based on principles of Artificial Intelligence (AI) and machine learning.

AERIAL-CORE[11]: Drones with Artificial Intelligence for maintenance of power lines

A research and innovation project of the Horizon 2020 Program led by Spain has developed drones with Artificial Intelligence (AI), capable of inspecting and manipulating lines in order to reduce maintenance costs for power lines, in addition to reducing accidents in the carrying out work that requires a certain height.

These drones have the ability to land automatically, even on the same cables, they can also manipulate with robotic arms. These drones can perceive the environment and change shape in flight to consume less energy to fly longer and longer distances. The project aims at a high European leadership in the field of robotics for the maintenance of infrastructures and facilities.

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[7] https://itea3.org/project/ai4pv.html.

[8] LCOE is a method to compare different generation technologies, which has been used by analysts to evaluate competitive technological options in the electricity market.

[9] https://itea3.org/project/eficas.html.

[10] https://itea3.org/project/defaine.html.

[11] https://aerial-core.eu/.