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# ITU-T L Suppl. 52 (10/2022)

SERIES L: Environment and ICTs, climate change, e-waste, energy efficiency; construction, installation and protection of cables and other elements of outside plant

# Computer processing, data management and energy perspective

ITU-T L-SERIES RECOMMENDATIONS

**ENVIRONMENT AND ICTS, CLIMATE CHANGE, E-WASTE, ENERGY EFFICIENCY; CONSTRUCTION, INSTALLATION AND PROTECTION OF CABLES AND OTHER ELEMENTS OF OUTSIDE PLANT**

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## Supplement 52 to ITU-T L-series Recommendations

### Computer processing, data management and energy perspective


### Summary

Supplement 52 to ITU-T L-series Recommendations proposes a set of good practices to improve the energy efficiency of cyber-physical applications – making use of Internet of things (IoT), artificial intelligence (AI), and digital twins. First, the Supplement introduces the cyber-physical paradigm, engineering reference framework, and a couple of system deployments models. Secondly, it defines three end-to-end use case typologies to be addressed (i.e., monitoring applications using smart IoT systems and AI software; smart applications using Edge computing and cloud data centre; and simulation applications using digital twin pattern). Energy efficiency practices are discussed adopting a circular value-chain model that consists of three main steps: data storage; data transfer/move; and data processing/analytics. Finally, this Supplement offers a set of recommended practices relating to each component of the three end-to-end use case typologies.



### History

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### Keywords

AI, big data, cyber-physical systems and applications, digital twins, energy efficiency, IoT.


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## 1 Scope

This Supplement presents a set of well-adopted energy efficiency practices for cyber-physical system classes and applications – enabled by artificial intelligence (AI), big data, Internet of things (IoT), and other innovative technologies.

To do so, a set of relevant and significant use cases are first introduced; Secondly, system classes are identified. Finally, according to a circular value-chain model, the system efficiency practices are specified and mapped to the components of the cyber-physical systems.

## 2 References

None.

## 3 Definitions

### 3.1 Terms defined elsewhere

This Supplement uses the following terms defined elsewhere:

**3.1.1 artificial intelligence** [b-ISO/IEC 2289]: Set of methods or automated entities that together build, optimize, and apply a model so that the system can, for a given set of predefined tasks, compute predictions, recommendations, or decisions. AI systems are designed to operate with varying levels of automation.

**3.1.2 big data** [b-ITU-T Y.3600]: A paradigm for enabling the collection, storage, management, analysis, and visualization, potentially under real-time constraints, of extensive datasets with heterogeneous characteristics.

**3.1.3 cloud computing** [b-NIST]: A model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction.

**3.1.4 cyber-physical systems** [b-NIST]: Smart systems that include engineered interacting networks of physical and computational components.

**3.1.5 data centre** [b-ITU-T L.1300]: A repository for the storage, management, and disseminations of data.

**3.1.6 deep learning** [b-ISO/IEC TR 24030]: Approach to creating rich hierarchical representations through the training of neural networks.

**3.1.7 digital twin** [b-W3C]: A type of virtual thing that resides on a cloud or edge node. Digital Twins may be used to represent and provide a network interface for real-world devices which may not be continuously online, may be able to run simulations of new applications and services before they get deployed to the real devices, may be able to maintain a history of past state or behaviour, and may be able to predict future state or behaviour.

**3.1.8 edge computing** [b-ISO/IEC TR 30164]: Distributed computing in which processing and storage takes place at or near the edge, where the nearness is defined by the system's requirements.

**3.1.9 energy efficiency** [b-ITU-T L.1310]: The relationship between the specific functional unit for a piece of equipment (i.e., the useful work of telecommunications) and the energy consumption of that equipment.

**3.1.10 infrastructure-as-a-Service (IaaS)** [b-IEEE SDN]: A platform supporting the resources needed by other layers. IaaS can be "programmed" by utilizing provisioning tools. Because of this programming interface, even if IaaS is often (but not only) made of "physical" resources, IaaS can be considered as a component.

**3.1.11 Internet of Things** [b-ISO/IEC 30141]: An infrastructure of interconnected physical entities, systems, and information resources together with the intelligent services which can process and react with information of both the physical world and the virtual world and can influence activities in the physical world.

**3.1.12 machine learning** [b-ISO/IEC DIS 19944-1]: Process using computational techniques to enable systems to learn from data or experience.

**3.2.13 platform-as-a-Service (PaaS)** [b-IEEE SDN]: Systems offering rich environments where to build, deploy, and run applications. PaaS provides infrastructure, storage, database, information, and process as a service, along with well-defined APIs, and services for the management of the running applications, such as dashboards for monitoring and service composition.

**3.1.13 sensor** [b-ITU-T Y.2221]: An electronic device that senses a physical condition or chemical compound and delivers an electronic signal proportional to the observed characteristic.

## 3.2 Terms defined in this Supplement

This Supplement defines the following term:

**3.2.1 big data analytics platform**: An ecosystem of services and technologies that needs to perform analysis on voluminous, heterogeneous, and dynamic data.

# 4 Abbreviations and acronyms

This Supplement uses the following abbreviations and acronyms:

| | |
|---|---|
| 5G | $5^{th}$ Generation of Wireless Networks |
| AI | Artificial Intelligence |
| API | Application Programming Interface |
| BRR | Best Resource Ratio |
| BD | Big data |
| CO2 | Carbon Dioxide |
| CPE | Customer Premises Equipment |
| CPU | Central Processing Unit |
| DCIE | Data Centre Infrastructure Efficiency |
| DL | Deep Learning |
| GPU | Graphical Processing Units |
| IaaS | Infrastructure-as-a-Service |
| ICT | Information and Communications Technology |
| IEC | International Electrotechnical Commission |
| IEEE | Institute of Electrical and Electronics Engineers |

| | |
|---|---|
| IoT | Internet of Things |
| ISO | International Organization for Standardization |
| ISP | Internet Service Provider |
| IT | Informational Technology |
| KPI | Key Performance Indicator |
| ML | Machine Learning |
| NLP | Natural Language Processing |
| OLT | Optical Line Termination |
| ONU | Optical Network Unit |
| PaaS | Platform-as-a-Service |
| PON | Passive Optical Networks |
| PoP | Points of Presence |
| PSU | Power Supply Unit |
| PUE | Power usage effectiveness |
| RAM | Random-Access Memory |
| UPS | Uninterruptible Power Supply |
| VLAN | Virtual Local Area Network |

## 5 Conventions

None.

## 6 Computer processing, data management and energy perspective

### 6.1 Introduction

By 2023, 5.3 billion people will have access to the Internet, up from 3.9 billion in 2015 [b-Cisco2020]. Data centres support the information technology (IT) equipment required to provide the services accessed by these billions of Internet users. Ranging from small cabinets to large warehouses hundreds of thousands of square metres in size [b-Shehabi1], data centres are designed to provide reliable access to power, cooling, and Internet connectivity for the IT equipment located within servers, networking, and storage [b-Mytton].

By 2021, there will be 7.2 million data centres around the world, down from 8.5 million in 2015 [b-Thibodeau]. This fall is due to the ongoing migration of computing resources to the cloud. In the past, customers bought and owned physical equipment which they were responsible for deploying into space leased from data centre operators. Most of the growth in usage is now in the cloud where customers buy units of computing, storage, and networking, paying based on usage by the second, hour, or per user request. The top three cloud providers by usage – Amazon Web Services, Microsoft Azure, Google Cloud Platform [b-Flexera] – make up the majority of the $236 billion cloud market [b-Adams], and are responsible for some of the largest data centre operations. These "hyperscale" cloud providers now operate 541 data centres as of 2020, with another 176 under construction [b-Synergy].

Estimates of global data centre energy consumption for 2020 range from 196 terawatt hours (TWh) [b-Masanet] to 287 (TWh) [b-Hinterman], and there is considerable variance in how this is expected to grow over the coming years. Some projections suggest that global data centre energy has plateaued and will grow by only 5% to 209 TWh in 2023 [b-Masanet]. Other projections suggest that data centres in China alone will use 266 TWh of electricity by 2023 [Greenpeace] and 96.2 TWh in the EU28 by 2025, 60% from cloud data centres [b-Montevecchi].

Although some of the uncertainty in these figures is due to rapid technological change, such as the introduction of new processors e.g., graphical processing units (GPUs) for machine learning; the growing numbers of Internet of things (IoT) devices [b-Shehabi2]; central processing unit (CPU) performance improvements and the impact of the end of Moore's Law [b-Leiserson], the range in figures also highlights another challenge: transparency. Moving to the cloud means customers no longer have any visibility into the resource consumption of their IT infrastructure [b-Mytton]. Whereas when customers purchased and ran their own IT equipment, they could directly calculate energy usage and embodied emissions, the data needed to make environmental assessments is not provided by the cloud vendors. This makes it difficult to begin to address data centre energy because the numbers needed to pinpoint areas of focus in the area with most growth are not available.

### 6.2 Cyber-physical paradigm (IoT, AI analytics, and digital twin innovative technologies)

Cyber-physical systems are smart systems that include engineered interacting networks of physical and computational components. Cyber-physical frameworks make use of much of the existing technologies (communication network technologies, information technologies, sensing/control technologies, software technologies, hardware/device technologies) and combine them to improve operations, lower costs, create new products and business models, enhance engagement and customer experience. Often, these frameworks are also referred to as Internet of things (IoT) or digital twin systems and applications.

Figure 1 depicts the archetype of cyber-physical frameworks.

Cyber-physical frameworks enable a very wide spectrum of applications and implement the integration of systems from different vertical sectors (enterprise, consumer, government, industries, etc.) [b-Bradford]. Cyber-physical application domains embrace: smart city, smart grid, smart home/building, digital agriculture, smart manufacturing, intelligent transport system, smart energy, and digital health, etc.

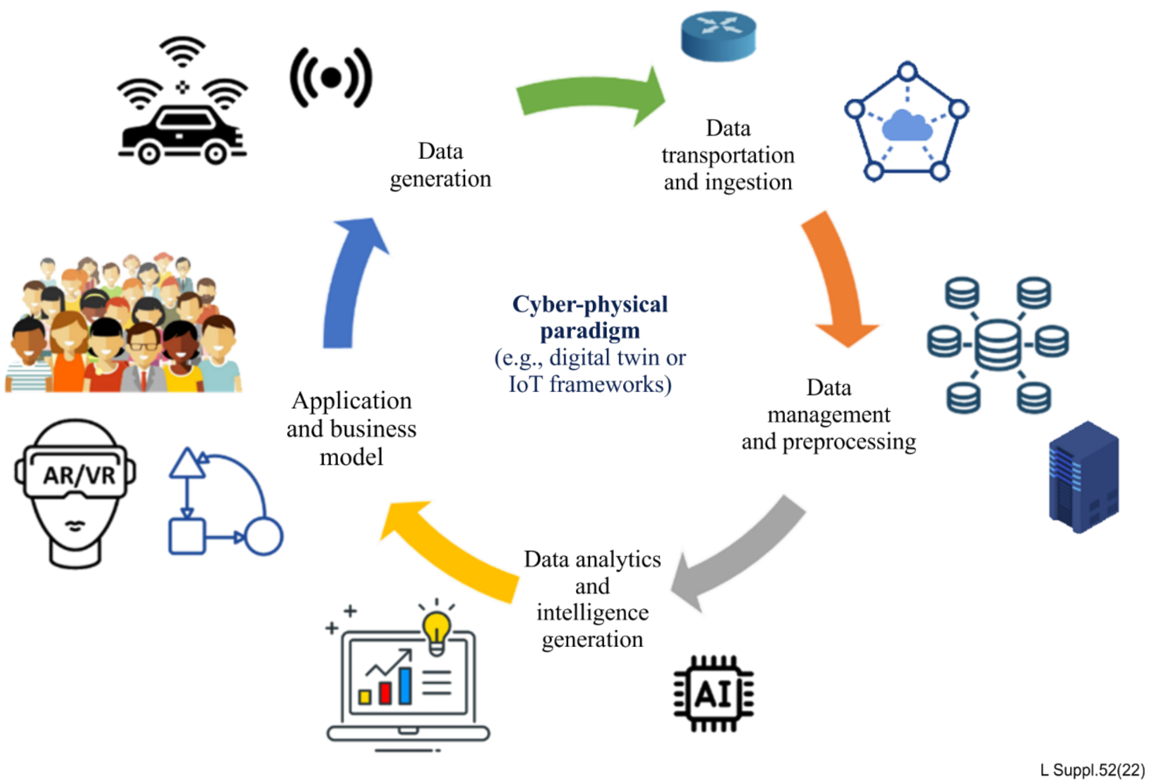


**Figure 1 – The archetype of cyber-physical paradigm**

### 6.3 Digital twin pattern

The digital twin communication pattern implements the cyber-physical paradigm; it has been around for several years in the manufacturing sector. Nowadays, due to the digital revolution of our society, it is getting more and more popular in the other sectors of our economy and society. The pattern is shown in Figure 2.

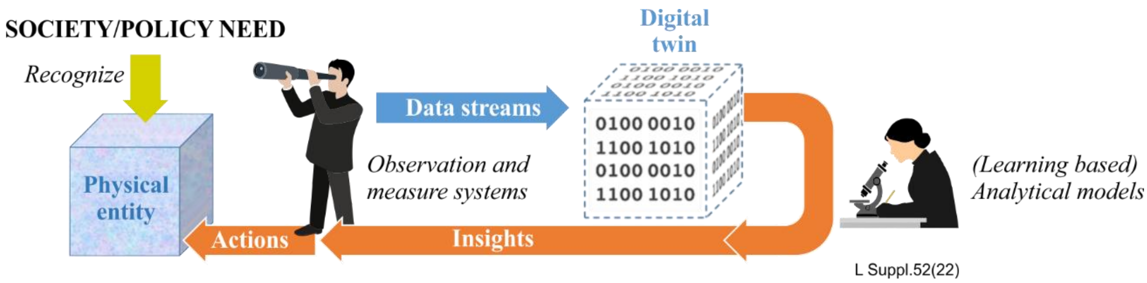


**Figure 2 – Digital twin communication pattern**

### 6.4 Cyber-physical reference framework

Mobile technology (e.g., 5G and the next 6G), cloud computing (e.g., cloud-based data centres and edge computing), big data and deep analytics (e.g., predictive, cognitive, real-time, and contextual) play important roles for cyber-physical systems and applications, by gathering and processing data to achieve the final result of controlling physical entities and impacting virtual entities [b-Bradford] [b-EuroCom1].

In a general setting, the cyber-physical platform reference framework considers the following five main digital components belonging to four different technology tiers [b-EuroCom1], which are depicted in Figure 3:

1) assets/sensors;

2) networks;

3) computing systems;

4) (big) data analytics platforms;

5) software applications.

The archetypal engineering architecture (or reference framework) of a cyber-physical (e.g., digital twin or IoT) platform is shown in Figure 3 [b-ITU-T Y.3502] [b-ISO/IEC 30141] [b-2020 SFR] [b-Lean ICT] [b-EuroCom3].

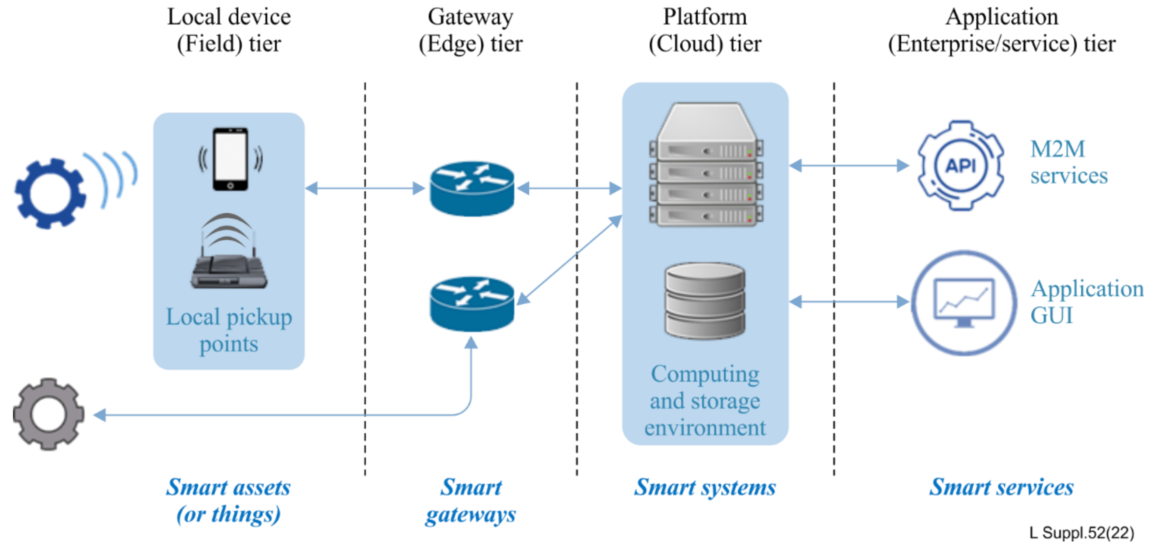


**Figure 3 – Cyber-physical architecture reference framework**

The field (or local device) tier consists of *smart assets* (e.g., sensors), while the gateway (or edge) and platform (or cloud) tiers contain *smart gateways* and *systems*, respectively. Finally, the application (or enterprise/service) tier manages smart *services* [b-EuroCom3] [b-energystar] [b-EuroCom4].

### 6.4.1 Smart assets (or things)

The local device (or Field) tier comprises different types of devices, ranging from a smart machine to a sensor or an actuator and representing the networked edge node. They are also called *smart assets* (or *things*) because they use information and communications technology (ICT) capabilities (such as network, computing, and storage) to implement autonomy and collaboration.

### 6.4.2 Smart gateways

The gateway (or edge) tier contains the edge gateways. These are computing devices (i.e., a functional unit that can perform substantial computations) that operate as connectors (e.g., by implementing network connection and protocol conversion) between the smart assets (i.e., the physical world local devices) and the digital world. Real-time data analytics is performed by these components. Wherever necessary, for security and transparency reasons, a digital ledger (for example by using block-chain technology) may be included.

### 6.4.3 Smart systems

The platform (or cloud) tier consists of computing servers (and software) that enable non-real-time analytics and manage the cyber-physical system as a whole, by orchestrating the diverse components and the required ICT capabilities, in order to enable the final application/service business logic. These smart systems are commonly constructed based on the collaboration of multiple distributed smart gateways and servers to support elastic expansion of network, computing, and storage resources, see virtual infrastructures and platforms. Cloud computing and edge computing servers are typical examples of smart systems.

#### 6.4.3.1 Cloud data centres and edge/fog computing systems

While cloud data centres are large facilities deployed in a limited number of locations (due to special infrastructure and management needs), in a digitally transformed society, cloud users are spread everywhere, IoT and 5G enabled applications are significant examples. Commonly, clients and users are far from the cloud data centres which are managed by their preferred providers. Edge and/or fog computing infrastructure are likely to be closer to those devices and applications to bring computing capacity with lower response time [b-EuroCom2]. Therefore, in the edge computing model an important part of computing and sometimes storage happens in the edge of the network and not in the cloud data centre.

In principle, this allows reduction of the data quantity to be moved around the network and distributes the computing load. Edge computing infrastructures connect the physical and the digital worlds enabling the development of smart systems and applications. While cloud computing effectively supports non-real-time and long-period data driven scenarios, edge computing is effective for real-time and short-period data driven scenarios, such as local decision-making. Commonly, edge computing does not replace cloud services but complements them, reducing storage requirements, decreasing latency, and providing real-time responses to users' and application requests.

"The edge" can be defined in several different ways. Some providers define their edge as a points of presence (PoP) in major cities. These PoPs may operate a complete copy of the system to offer all functionality, located closer to the user for lower latency and reduced data transfer. PoPs may be located in in major Internet exchanges (IXs) such as in LINX (London), AMS-IX (Amsterdam), DE-CIX (Frankfurt), JPNAP (Tokyo). Other providers operate a subset of their platform functionality, such as popular content caching, in a large number of PoPs. These may be deployed in Internet service provider (ISP) networks much closer to the user, such as in the telephone exchange in the closest town, or near to radio cell towers. For example, Google has three layers to its network and the most granular edge caching nodes are deployed close to major population centres with multiple nodes within countries, not just in the main IXs [b-Google2020] .

### 6.4.4 Smart services

The application (or service) tier contains the business logic software that generates and exposes actionable intelligence to the cyber-physical system users and clients. The business logic software makes use of smart systems functionalities. Cyber-physical smart services range from observation and monitoring to decision-making and simulation.

## 6.5 Cyber-physical system deployment models

According to the end-to-end application considered, the cyber-physical computing architecture, depicted in Figure 3, can be deployed using either a three-layer or a four-layer model [b-EuroCom4].

### 6.5.1 Cyber-physical architecture three-layers deployment

A three-layers model is common for application scenarios where smart services are distributed, i.e., deployed in one or more scattered areas, each of them characterized by a low traffic volume. Most of data processing is done at run-time by the smart gateways and the cloud-enabled service environment is used to enable services distribution and reach user devices. Smart systems are not deployed in a dedicated layer (not much data exchange and secondary processing are needed) but are part of either the gateway or the service layers [b-Bradford] [b-EuroCom1] [b-EuroCom4].

**Smart assets** are processed locally by the **smart gateways**, which provide real-time streaming data analysis. In addition, the smart gateways aggregate multiple and heterogeneous data streams sending non-real-time data to the cloud for storing and possible additional processing. Finally, each smart gateway implements network services (notably, access to and local management of smart assets), security services, and small-scale local data storage.

Typical examples of these application scenarios are: smart devices monitoring and control, and smart environmental protection. The three-layer deployment model is shown in Figure 4.

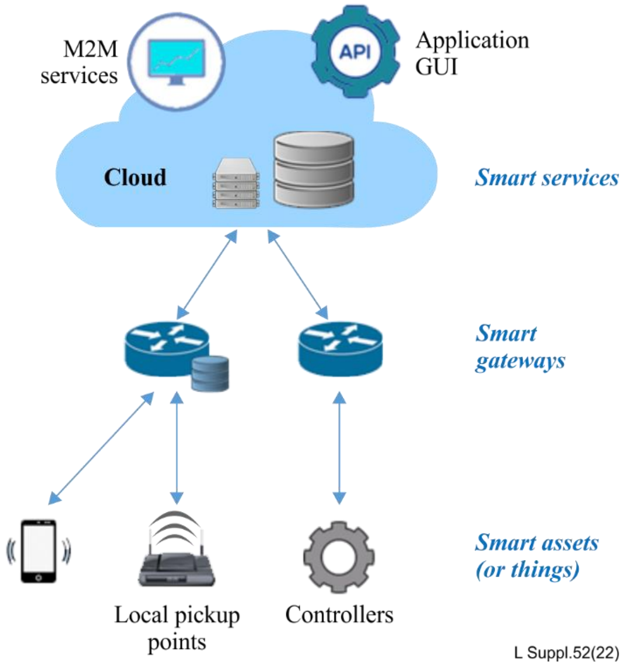


**Figure 4 – Three-layers deployment schema of cyber-physical architectures**

### 6.5.2 Cyber-physical architecture four-layers deployment

A four-layers model is common for application scenarios where smart services are deployed centrally, and the traffic volume is high [b-EuroCom4]. A large amount of data and many local application systems are deployed at the edge of the network. Therefore, it is necessary to provide a large amount of computing and storage resources near the edge, i.e., distributed smart systems. This is achieved by deploying a layer consisting of a set of locally distributed smart systems. They are in charge of aggregating data for secondary processing; the primary processing, the real-time one, was already done by the smart gateways and the smart assets. The locally distributed smart systems are interconnected to exchange data and knowledge. These (commonly cloud-based) systems support horizontal elastic expansion of computing and storage resources and implement real-time decision-making and optimization operations locally [b-Bradford] [b-EuroCom1] [b-EuroCom4]. The service environment (cloud-enabled) is then used to connect with users, see ubiquitous Internet connection.

Typical examples of these application scenarios are video analysis, distributed grid, and smart manufacturing. The four-layers deployment model is shown in Figure 5.

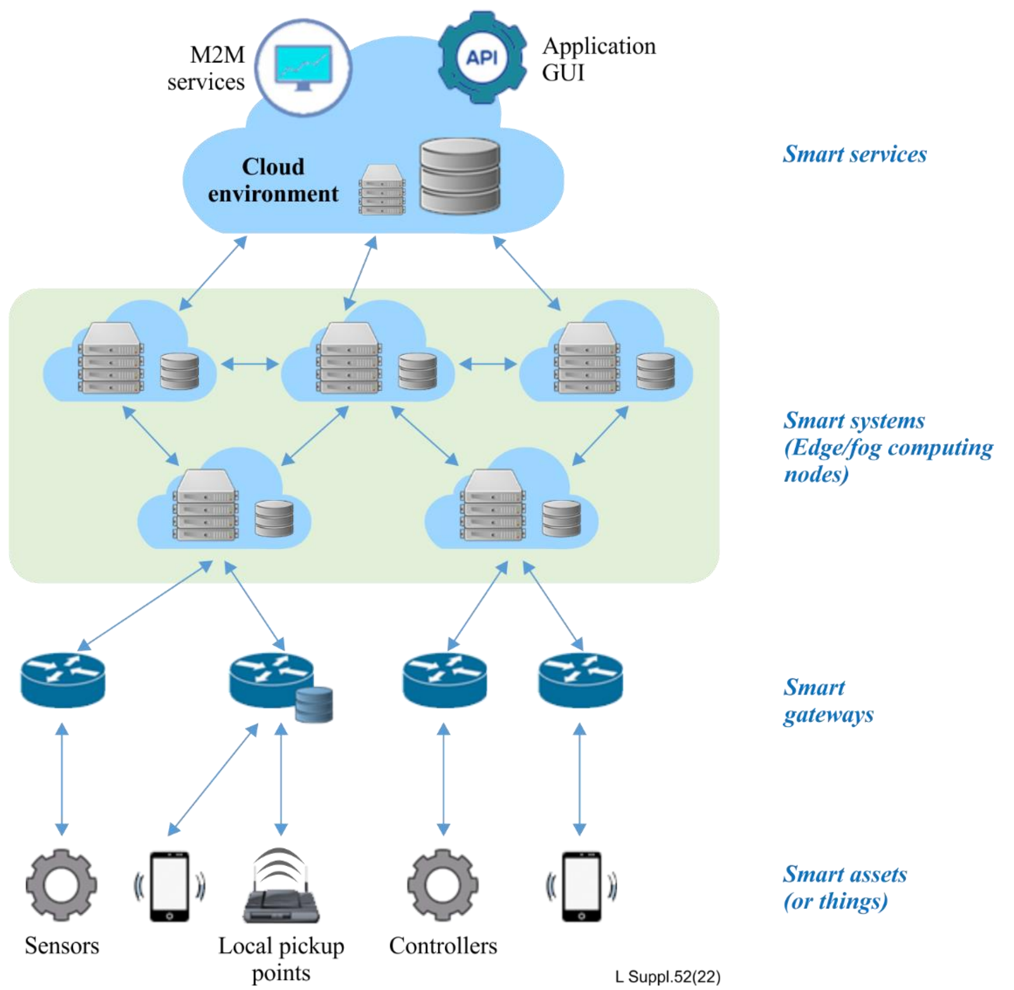


**Figure 5 – Four-layers deployment schema of cyber-physical architectures**

### 6.5.2.1 Cloud environment deployment

Cloud platforms can be public, private, and hybrid. In particular, a cloud can be seen as an extension of an enterprise data centre (i.e., a private facility operated for the sole use of supporting a single organization), see Figure 6.

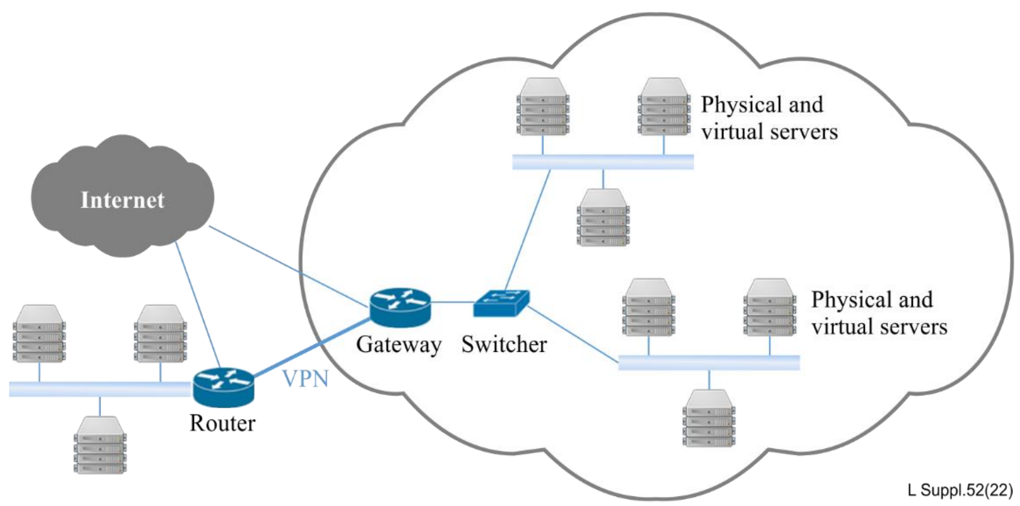


**Figure 6 – Cloud as an extended enterprise data centre**

Cloud platform performances depend on various cloud-services operation factors including [b-ISO/IEC 30141]:

- availability of the service;
- response time to complete service requests;
- transaction rate at which service requests are executed;
- latency for service requests;
- data throughput rate (input and output);
- number of concurrent service requests (scalability);
- capacity of data storage;
- (for IaaS and PaaS) the number of concurrent execution threads available to an application;
- (for IaaS and PaaS) the amount of random-access memory (RAM) available to the running program;
- data centre network IP address pool and/or virtual local area network (VLAN) range capacity.

Cloud energy consumption is influenced by its performances and, hence, its implemented services and operations.

## 7 End-to-end use cases addressed

For the scope of this Supplement, we distinguish three different types of cyber-physical use cases, building on a combination of innovative technologies:

1) monitoring applications using smart IoT systems and AI software;
2) smart applications using edge computing and cloud data centre;
3) simulation applications using the digital twin pattern.

For these use case typologies, we analyse the energy perspectives related to their computer processing and data management aspects.

### 7.1 Monitoring application using smart IoT systems and AI software

These applications commonly implement a three-layers deployment schema, see Figure 4.

### 7.2 Smart application using edge computing and cloud data centre

Smart applications and systems build on the collaboration of multiple distributed smart servers that connect the physical and the digital world providing real-time data analysis and actionable intelligence, see the cyber-physical systems and the digital twin pattern.

These applications commonly implement a four-layers deployment schema, see Figure 5.

### 7.3 Simulation applications using digital twin pattern

These applications commonly implement a four-layers deployment schema, see Figure 5.

## 8 Energy efficiency criteria

This clause aims to give an overview of the energy efficiency criteria applicable to the use cases studied in this Supplement. The purpose of this analysis is to give objective and quantitative energy efficiency criteria for the ICT goods, networks and services used in the use cases. In the case of goods, networks and services without available quantitative energy efficiency standards, the best available technologies present in the market, that can potentiate the energy efficiency in the AI and emerging technologies studied, will be outlined.

The Energy Efficiency Directive 2012/27/EU of the European Parliament and of the Council of 25 October 2012 [b-Nativi] outlines the definition of energy efficiency as the "*ratio of output of performance, service, goods or energy, to input of energy*." in line with the energy efficiency general definition used in ITU-T documents, such as Recommendation [b-ITU-T L.1330].

### 8.1 Adopted methodology

The methodology chosen to accommodate the different measures within a certain use of an ICT good, network or service, was to consider a circular value-chain process consisting of three main steps:

a) Data storage

b) Data transfer/movement

c) Data processing/analytics

The concept is that each of these stages of data management and use have different energy efficiency criteria and needs and will be analysed individually.

For the most part, the functionalities that make up the technologies in the study, such as AI or other emerging technologies, depend on current ICT goods and networks, albeit with different configurations originating from the innovative aspect of these technologies. For this, the ICT goods and networks outlined in the following paragraphs represent the best available practices and technologies in the field, so that this technical report may endure the test of time.

### 8.2 Data storage

Regarding data storage, data centres were considered as these structures are computer warehouses that store a large amount of data for different organizations to meet their daily transaction processing needs. They contain servers for the collection of data and network infrastructure for the utilization and storage of the data.

#### 8.2.1 Metrics and criteria

##### 8.2.1.1 Power usage effectiveness (PUE) and data centre infrastructure efficiency (DCIE)

The metric commonly used by the ICT industry to identify the energy efficiency of a data centre is the PUE, which is the ratio of total data centre input power to IT load power. A higher PUE means that more energy is used by the supporting infrastructure such as lighting, cooling, and power distribution rather than energy going to IT equipment. PUE has been criticized as a measure of efficiency because it only considers energy usage and was intended only as a site-specific metric rather than one used for comparison between facilities. PUE may decrease when IT load increases because the IT equipment is drawing more energy, even though the efficiency of the data centre has not actually improved [b-Brady].

The ideal value of PUE is 1.0 which indicates all energy goes to the IT equipment. However, this is generally not attainable at present due to the consumption of electricity by uninterruptible power supply (UPS), fans, pumps, transformers, lighting, and other auxiliary equipment in addition to the consuming IT load.

The most efficient data centres are approaching low values, such as EcoDataCenter in Falun, Sweden, which has a PUE of 1.15 [b-EcoDataCenter], and Google's fleet of data centres which achieved a Q2 2020 trailing twelve-month global average of 1.10. However, there are indications that PUE improvements are plateauing [b-Lawrence].

PUE has been shown to correlate poorly with carbon emissions [b-Lei], so should not be the only metric tracked [b-Whitehead]. Another metric used to measure the data centres' efficiency is the DCIE, which is expressed as a percentage and is calculated by dividing IT equipment power by total facility power (DCIE = IT equipment power/total facility power x 100%).

The EU Code of Conduct for Data Centres [b-Leiserson], a voluntary programme, has been created in response to the increasing energy consumption in data centres and the need to reduce the related environmental, economic and energy supply impacts and with the aim to inform and stimulate operators and owners to reduce energy consumption in a cost-effective manner and without hampering the critical function of data centres. In a 2017 report by the JRC on the trends in data centre energy consumption under the Code of Conduct, an overview is given of a decrease of the average PUE of data centres through the years for the entire 289 data centres sample. Some best practices on ways to improve the overall PUE of data centres are given [b-Acton1] [b-ITU-T L.1300], such as free cooling technologies (direct and indirect air, direct and indirect water) or project management procedures that can be implemented and have a positive impact in the overall efficiency of the structures.

#### 8.2.1.2 Energy efficiency in PSU

An example of an energy efficiency criterium applicable to the data storage stage may concern the power supply unit (PSU). Regarding the PSU, the EU regulation on eco-design requirements for servers and data servers and data storage products, outlines that from 1 January 2023, for servers and online data storage products, with the exception of direct current servers and of direct current data storage products, the PSU efficiency at 10%, 20%, 50% and 100% of the rated load level and the power factor at 50% of the rated load level shall not be less than the values reported in the table shown in Figure 7.

**Minimum PSU efficiency and power factor requirements from 1 January 2023**

| | Minimum PSU efficiency | | | | Minimum power factor |
|---|---|---|---|---|---|
| % of rated load | 10 % | 20 % | 50 % | 100 % | 50 % |
| Multi output | – | 90 % | 94 % | 91 % | 0.95 |
| Single output | 90 % | 94 % | 96 % | 91 % | 0.95 |

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**Figure 7 – Minimum PSU efficiency and power factor requirements from January 2023[1]**

### 8.2.2 Energy efficiency best practices on data storage

Data storage with a 'data storage product' means a fully functional storage system that supplies data storage services to clients and devices attached directly or through a network. [b-ISO/IEC 30141]

Both Energy Star [b-Nativi] and the EU Code of Conduct for Energy Efficiency in Data Centres [b-Acton1] present a set of energy efficiency measures that can be implemented in data storage facilities. The concepts included concern making better use of existing storage hardware, reducing the volume of data to be stored and using storage equipment that consumes less energy.

Concerning making better use of existing storage hardware, **storage tiers** are outlined as the assignment of different categories of data to various types of storage media, with the ultimate goal of reducing the storage cost. These tiers are determined by performance needs, the cost of the storage media, and how often this data is accessed. There is a defined grading system on the tier storage policies where the most frequently accessed data are placed on the highest performing storage, whereas the rarely accessed data go on low-performance, cheaper storage.

**Storage virtualization** is another measure to improve energy efficiency in the storage stage. Storage virtualization is the pooling of physical storage from multiple network storage devices into what appears to be a single storage device that is managed from a central console. Storage virtualization enhances storage performance, enables the use of storage tiers, and makes it easier to expand storage capacity.

1 Source: Regulation on eco-design requirements for servers and data storage products EU 2019/424.

**Thin provisioning** presents an application with a virtual volume of just about any size but allocates physical storage space on a just-enough, just-in-time basis by centrally controlling capacity and allocating space to an application as data is actually written.

Another big part of energy efficiency in data storage measures relies on the reduction of the volume of data to be stored. **Data compression** is performed by software that uses a formula or algorithm to determine how to shrink the size of the data. Compression functionality is built into a wide range of technologies, including storage systems, databases, operating systems, and software applications used by enterprise organizations.

**Deduplication software** works by retaining one unique instance of a file or data block and replacing all duplicates with a pointer to the original.

**Snapshot technology** is another measure that can be applied in order to save energy in the storage stage. Snapshot technology works so as to avoid downtime, instead of making a full backup of the data, high-availability systems may instead perform the backup on a snapshot, a read-only copy of the data set frozen at a point in time, and allow applications to continue writing to their data. Snapshots create temporary virtual "copies" of data that only include data changes.

Not specifically related to data centre storage but very important are other strategies such as the **decommissioning of unused servers and the consolidation of lightly utilized servers**, can also be measures to be implemented since often, data centres, possess aged and unused servers that are still running. The **management of airflow** is an important aspect of data centre energy optimization. Some of the best practices include the redefinition of the server racks into a **hot aisle/cold aisle layout**, where the rows of server racks are oriented so that the fronts of the servers face each other instead of being in the same air flow direction.

The **containment/enclosures** arrangements when used in combination with the hot aisle/cold aisle layout can also improve the efficiency of data centre server rooms. This containment refers to the various physical barriers that eliminate the mixing of cold air with hot air coming out of the server racks. This configuration allows for higher temperatures in the server rooms, which saves energy due to the slowing down of the fan speeds and increase of chilled water temperatures and the increase of the use of free cooling techniques.

Another measure that can be implemented within the design of data centres is the introduction of variable speed fan drives of computer rooms' air conditioning and can be adjusted on the demand of the data centre which is constantly changing.

Finally, Energy Star indicates **properly deployed airflow management devices** such as the positioning of diffusers, blanking panels, structured cabling systems, the elimination of sub-floor obstructions, floor grommets and the correct placing of vented tiles as measures to improve the overall efficiency of the data centre under the management of airflow measures.

### 8.3 Data transfer – 5G, wireless, and copper networks

This clause aims to evaluate the best available technologies regarding data transfer and networks. The scope of this clause is to evaluate the network technologies and data transfer protocols aiming for a better energy efficiency in the use cases studied.

Regarding mobile networks, the **5$^{th}$ generation,** or **5G,** will greatly contribute to the accomplishment of the expectations of the IoT ecosystem and all its interdepending stakeholders in terms of accessibility and network speeds.

5G has been studied to be up to 90 percent more energy efficiency per traffic unit than legacy 4G networks, with several hardware and software solutions that help to save energy. However, experts expect, similarly to what happened with other technologies before, that the deployment of 5G network will lead to an increase of energy consumption. With companies expecting to be increasing their energy consumption due to an increase of traffic, the technology needs to be rolled-out in a way that the higher energy consumption of this technology is met with beneficial measures that minimize this increase. Some of the measures outlined in a recent position paper [b-Ericsson] that may contribute to a smoother and more efficient technology transition are:

- **Prepare the network**: Which includes the replacement of existing networks instead of adding new ones;
- **Activate energy-saving software**: Which refers to energy saving features in the 5G network components, such as micro-sleep functions;
- **Build 5G with precision**: Which concerns the avoidance of over-dimensioning hardware by considering the needs of the area of installation, to save on energy and costs;
- **Operate site infrastructure intelligently**: Including the use of artificial intelligence to operate site infrastructure.

On another aspect, currently, the impact of **wireless networks** on the energy footprint of the ICT sector, could be said to be quite small due to the protocols that are used. Nevertheless, as more and more traffic being transferred towards wireless networks, and with the IoT being heavily dependent on wireless technologies, traffic is also increasing, thus making the energy efficiency of such communications non-negligible.

For example, in an evaluation with four of the most popular IoT protocols (Zigbee, LoRa, Bluetooth and WIFI) that constituted a wireless sensor network, in a smart campus experience [b-Del-Valle], an assessment of the energy efficiency of these protocols was performed. With a network of sensors being composed of sensors, radio transmitters and receivers, CPU and memory and the power source (battery), the authors identified some issues that can affect the node battery consumption. The term unbalanced energy depletion is presented and describes a situation where the nodes that are closer to the coordinator node carry more traffic, and so they consume more energy than those nodes further away from the root node. This imbalance causes the overall energy to be distributed non-uniformly in the network, making some nodes run out of power faster than others. Looking at the energy side of the networks, the authors have identified that this is an important issue in the warranty of stable networks, due to the life of batteries. The IoT protocol found by the authors, in this network, to be the most efficient protocol was Zigbee, both in a cooperative and collaborative configuration of the network.

### 8.3.1 Energy efficiency of 5G

The introduction of 5G into the networks with 2G, 3G and 4G will most probably bring more power consumption [b-ITU FG-AI4EE D.WG3-2]. Moreover, though 5G can provide faster and more numerous services, its energy efficiency is not always optimal, especially at the initial stage of deployment or with low traffic. On the other hand, it is possible to re-use the 4G energy saving practices and technologies (e.g., carrier shutdown, channel shutdown, symbol shutdown, etc.) [b-ITU FG-AI4EE D.WG3-2], while enhanced technologies have been developed in the 5G era (e.g., deep sleep, symbol aggregation shutdown, etc.). Finally, big data and AI must be further utilized to implement intelligent and self-adaptive energy saving solutions and strategies, based on specific site traffic and other site-related conditions. According to [b-ITU FG-AI4EE D.WG3-2] an AI-driven smart procedure for energy saving includes the following steps:

1) **Data acquisition**: The network performance data and MR/ CDT data of the base station are obtained through network management or data acquisition system.
2) **Data processing**: The collected data are pre-processed as being cleaned, constructed, aggregated and screened as training data for scene recognition, load forecasting and other models.
3) **Scenario identification**: The machine learning algorithm is used to identify the application scenario and determine the energy-saving shutdown scheme and function.

4) **Threshold determination**: According to the energy-saving target to be achieved, the appropriate energy-saving threshold is determined.

5) **Time-span determination**: Based on the historical traffic data, the machine learning algorithm is used to predict the traffic load in a certain period of time in the future to determine the energy saving time and activate the time window.

6) **Execution strategy**: The integrated energy-saving strategy is sent to the network management system to perform the energy-saving operations on 5G base station, such as deep sleep, carrier shutdown, symbol shutdown and corresponding activation time window.

7) **Feedback and optimization**: The performance data of the base station are collected to evaluate whether the expected target is achieved or not, and the closed-loop iterative optimization threshold strategy is adopted.

Naturally, in addition to network traffic monitoring, there are also AI techniques for traffic forecasting.

### 8.3.2 Energy efficiency best practices with passive optical networks

Communication networks are responsible for a great amount of energy consumption in the ICT ecosystem. Passive optical networks (PON) are important to take into consideration when addressing energy efficiency practices. One of the most promising methods to save energy in fibre access networks is to put network devices, such as an optical network unit (ONU) or optical line termination (OLT) or parts of them, into sleep mode when there is no traffic to be transmitted. However, putting these devices into sleep mode may incur packet delays. Ultimately, to save energy in passive optical networks, using efficient energy management with scheduling for the sleep and wake up periods is a challenging though rewarding task.

Energy saving of optical networks in four different levels are addressed in [b-Zhang]; components, transmission, network and applications.

- **Component** level, integrating all-optical processing components such as optical buffers, switching fabrics, and wavelength converters, may significantly reduce energy consumption.
- **Transmission** level, low-attenuation and low-dispersion fibres, energy-efficient optical transmitters, and receivers (which improve the energy efficiency of transmission) are also being introduced.
- **Network** level, energy-efficient resource allocation mechanisms, green routing, long-reach optical access networks, etc. are trying to reduce energy consumption of optical networks.
- **Application** level, mechanisms for energy efficient network connectivity such as "proxying" and green approaches for cloud computing are being proposed to reduce energy consumption.

As referred to in [b-Valcarenghi], several solutions to reduce energy consumption in ONUs have been proposed by many researchers so far. The article refers to that for time-division multiplexed (TDM) PONs with sleep mode, an ONUs' energy consumption can be reduced by switching it to low power mode when idle. However, huge savings can only be achieved if ONUs are capable of quickly regaining synchronization upon wake up, and the power consumed while sleeping is much less than when the ONU is on. Moreover, data link layer solutions alone (e.g., sleep mode) may be effective when network utilization is low, but when network utilization increases, physical layer support (e.g., quick resynchronization) is necessary. If solutions and ONU architectures with such characteristics are developed, huge energy savings and limited delay increases can be achieved.

### 8.3.3 Energy efficiency best practices with copper networks

The ecological footprint of broadband access technology has substantially increased during the last decades due to the rapid acceptance and availability of fast and reliable Internet connections. With this an increase of energy consumption in these networks has also been detected. Despite the fact that there is a clear trend to more fibre-based access solutions in the future, DSL-based access will remain relevant.

There are several initiatives, such as the EU Code of Conduct Energy Consumption of Broadband Equipment [b-Acton2] and others that have been addressing the issue of energy consumption and urging the ICT industry to act on its environmental impact.

DSL is a cost-effective solution to bring broadband access to its customers by using the existing copper infrastructure, originally installed for simple voice communication.

The article on improving the energy efficiency of broadband copper access networks [b-Guenach] outlines some conclusions on best practices to be implemented in broadband networks: At the architecture level, by moving to **smaller nodes**, and at the component level, by selecting energy-efficient technology and/or by introducing **design techniques** (for instance, **clock and power gating**), which benefit from the typical Internet usage (burstiness of traffic, video streaming, day/night cycles), power savings can be obtained, which, in the best case, can reduce by more than half the energy consumption of the access network. Moving to a more distributed access network of small nodes is currently necessary with the introduction of G.vector and the planned introduction of G.fast, how these nodes can be cooled (fresh air cooling, passive cooling) and powered (reverse powering) can be reconsidered because of the different scales of these nodes. Some of these solutions not only provide energy saving but also assist in enabling the operator to easily deploy these increased numbers of small-sized active components in this network. For instance, by removing the need of active cooling (requiring additional power) in the small nodes, the power budget to feed these small nodes comes within reach of new power schemes such as **reverse powering** (which do introduce some inefficiency compared with classical powering schemes such as local ac/dc conversion).

The EU Code of Conduct outlines also that "the volume of deployed broadband equipment is increasing dramatically and so is its combined power consumption. Due to low customer aggregation ratios (typically, one customer premises equipment (CPE) per customer), such equipment is typically idle most of the time, most of the time exchanging data only to maintain its network status. It is therefore evident that such equipment can be optimized in terms of its power consumption and activity profiles. Examples of such techniques include **dynamic adaptation** (e.g., performance scaling), **smart standby** (e.g., through proxying network presence and virtualization of functions) and **energy aware management**."

## 8.4 Data processing

On data processing, there are several groups of ICT goods that can be evaluated. At first, computers and small servers are the ones that may present as the more obvious as these will be responsible for a great part of data processing with the roll-out of the emerging technologies, with the data being processed in cloud or edge computing.

The European Commission's regulation on Ecodesign requirements for computers and servers from 2014 outlines some guidelines for desktop computers, integrated desktop computers, notebook computers (including tablet computers, slate computers, and mobile thin clients), desktop thin clients, workstations, mobile workstations, small-scale servers, and computer servers. These types of hardware are ultimately expected to be responsible for a big part of the processing of data within the IoT environment. The Ecodesign requirements are presented in Annex II of the Guidelines [b-Craglia].

### 8.4.1 Energy efficiency best practices on data processing

There are several cases of energy efficiency in the different parts of the life of a byte of data that have been studied, especially in terms of the hardware or the infrastructures being used. An area that is still less investigated is the role that coding, and software can have in the energy performance in the data processing stages.

A study on the empirical evaluation of two best practices for energy-efficient software development [b-Procaccianti]**Error! Reference source not found.** evaluated the impact of two best practices for energy-efficient software and applied these practices in two widely used software applications, MySQL Server and Apache Webserver and each practice successfully reduced the energy consumption of our test environment and concluded that software design and implementation choices significantly affect energy efficiency. This study is based in previous studies that have been evaluating the connection between software development and energy efficiency, like the work of [b-Capra], which analyses the impact of application development environments over the energy efficiency of software applications, concluding for example that a high framework entropy is beneficial for the energy efficiency of small and medium applications. The work of [b-Sahin] which investigates the energy impact of using software design patterns and concluded that the impact of applying a design pattern varies greatly, from less than 1% to more than 700%. The work of [b-Noureddine] analyses the energy impact of programming languages and algorithmic choices that finds that the algorithm choice has a significant impact on energy consumption. (The recursive algorithm is more energy-efficient than the iterative one) and that the chosen programming language has a significant impact on energy consumption as well. [b-Manotas] investigated the energy impact of web servers in web applications and found that the energy consumption of a web application greatly varies depending on the chosen web server and that the variation depends on the specific feature of the web server. The same web server might be more energy efficient in a specific scenario (e.g., search) and very inefficient in others.

Another article analysing energy efficiency optimization in big data processing platforms by improving resources utilization [b-Song] outlines a proposal for the resources utilization in big data processing by allocating different resources according to a task-related best resource ratio (BRR), such as "CPU, disk, network in the ratio of 1:2:4", rather than the resource's quantity, such as "CPU = 1 GHz, network = 20MB/s". The study deduces the BRR of data processing tasks, and designs a resource ratio based approach ($R^2$), which includes a task scheduling algorithm and resource allocation algorithm, for energy efficiency optimization. Experiments show that the $R^2$ approach can improve energy efficiency by 10%.

In 2011, Intel produced a white paper on energy-efficient software guidelines, which can be help developers aiming to reduce the energy consumption of their pieces of software [b-Intel].

### 8.4.2 ML energy consumption and efficiency

Power models are built to design better hardware, design better algorithms or design better software to map these algorithms onto hardware.

In the case of ML applications, at the system-level, it is possible to distinguish between two power estimation models [b-García-Martín]:

- **Software level**: The focus is on the energy consumption of the application or software implementation and explore optimization techniques, working at the level of: application (for example, kernel sizes in a neural network); instructions (for example by using performance counter profiling, understand the cost for each instruction and try to reduce the most expensive part of the code);
- **Hardware level**: The focus is on the energy consumption of specific hardware components (for example, processor, memory and IO peripherals).

A general survey of the utilized techniques for both software and hardware levels is provided in [b-García-Martín]

In machine learning we can further distinguish two main phases: training and inference (or operational). Research settings typically focus on model training and accuracy performance. In industrial settings, the cost of inference might exceed the training costs in the long term. In this context, it might be more beneficial to use more expensive models to train even if they are more efficient in the inference phase, when in operation.

**Motivation: In the context of deep neural networks** regarding the training of some machine learning algorithms, the process generally involves a certain number of passes through the dataset, often called epochs. It has been realized in a recent study that there is a threshold of epochs at which the accuracy of machine learning models reached a plateau, but energy consumption continues to increase. The same for larger training data sets that demand more energy to train but do not lead necessarily to a proportional benefit in accuracy. The study suggests that there may be a path for models not reaching full accuracy and still complying with the needs of the user. Another suggestion was to use transfer learning where an existing model could be repurposed for a different task in order to save energy and time.

Advances in techniques and hardware for training deep neural networks have recently enabled impressive accuracy improvements in image processing and across many fundamental natural language processing (NLP) tasks as referred to in [b-Strubell], with also a great dependence of large computational resources that need similarly substantial energy consumption. In this clause we are mainly focusing on deep learning algorithms, as it is the set of techniques creating the most power consuming models today. However it is worth noting that this is just a subset of machine learning algorithms, and practitioners should also be encouraged to resort to more traditional and power-efficient options (such as random forest or XGBoost) when appropriate.

Some of the actionable recommendations to reduce costs in NLP that could be adapted in other applications, mentioned by the paper include:

- The reporting of training time and sensitivity to hyper parameters where it would be beneficial to directly compare different models to perform a cost-benefit (accuracy) analysis
- Prioritize computationally efficient hardware and algorithms

Most recently, some research developed within Google has also raised awareness of the high computational needs and other ethical risks of the latest NLP models [b-Bender], which has put some pressure on Google researchers to emphasize the importance of the topic and justify how the benefits of the model outweigh the energy costs. This other study [b-Patterson] shows how depending on the choices made for training a large NLP model, like the type of ML model, data centre and processor; the carbon footprint can be reduced up to ~100-1000X.

**How to estimate emissions**

The research community is increasingly asking for a systematic way of reporting the energy and carbon footprints of machine learning models [b-Henderson], and is also calling to direct research towards more efficient models focusing on what is called green AI, to decrease its carbon footprint and increase its inclusivity [b-Schwartz]. On the other side of the balance we have, what is defined here as red AI, which is AI that targets accuracy using massive computational power.

There are already some efforts to reduce the size of these models through techniques such as distillation or quantization [b-Hinton] [b-Zafrir]. They still however rely on a significant amount of processing to produce these reductions. Sparsely activated models have claimed to provide significant savings both for training and inference [b-Fedus].

In the recent years, some tools, such as the green algorithms tool [b-Fedus] or the **machine learning emissions calculator** [b-Lacoste], have been created that help machine learning researchers and practitioners get an understanding of the approximate environmental impact of their experiments. They based their estimations on the location of the server used, the length of the procedure, and the make and model of the hardware. In [b-Bender] the authors present the state-of-the-art approaches and software tools used to estimate energy consumption from machine learning algorithms up to mid-2019.

However, being able to approximately measure while running the experiments is generally more accurate than indirect estimations a posteriori. At the end of 2019, [b-Lottick] presented a python package that calculates the energy and C02 emissions of any (python) function and provides an

**energy usage report** to add context to these results, see Figure 8. Another attempt presented a month later is the **experiment-impact-tracker** framework [A11], which provides a systematic way for the community to consistently account and report energy, computing, and carbon metrics. This tool can make it easier to understand the full training lifecycle, including training attempts performed before the set up used as the final one. Most recently **CodeCarbon**[2] is also being developed to approximately measure carbon emissions in a more automatic way.

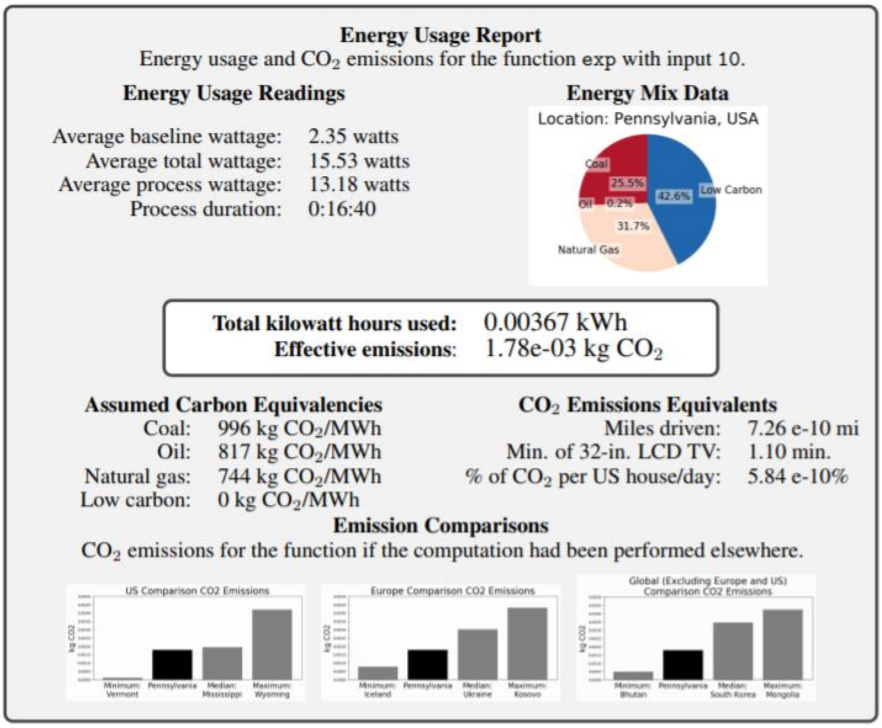


**Figure 8 – Energy usage report for a simple exponential function.**
(Image taken directly from***Error! Reference source not found.*** [b-Peter])

**ML on edge devices**

More and more computation is gradually taking place on edge devices (i.e., IoT), thanks to the explosive growth of Internet-connected devices. Edge devices are power or resource-constrained, and typically a trade-off between accuracy and efficiency must be found. An article on energy-efficient machine learning on the edges [b-Kumar] also considers **new hardware architecture** for machine learning on edge and **hardware-based full stack optimization** for machine learning on edge computing as two categories that can be exploited in order to meet the growing demand for resources in machine learning algorithms.

The same applies at the **software level and packages** where now many projects focus on developing and optimizing software platforms and machine learning packages to meet the low-power requirements of the edge. **Algorithms**, again, are seen as a key path to reducing the energy consumption of machine learning models, being by reducing the computational requirements, by the reduction of the accuracy of operations and operands.

In order to address the issue of the large environmental impact of such **AI training processes**, some solutions have been outlined [b-Cai] such as a **once-for-all** network, which trains a large model that has many **pre-trained sub-models** of different sizes that can be tailored to a range of platforms without retraining.

2 https://github.com/mlco2/codecarbon

Each of these sub-models can operate independently at inference time without retraining, and the system identifies the best sub-model based on the accuracy and latency trade-offs that correlate to the target hardware's power and speed limits.

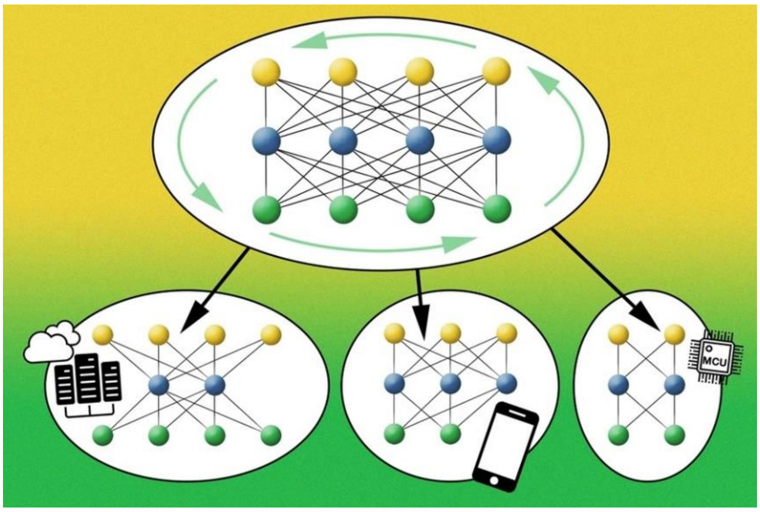


**Figure 9 – Neural network with sub-models. Source: MIT [b-MIT]**

A "progressive shrinking" algorithm trains the large model to support the sub-models at the same time. First, the large model is trained and then the smaller sub-models are trained with the aid of the large model so that they learn simultaneously. Finally, all of the sub-models are supported, allowing for a speedy specialization based on the target platform's specifications.

**Summary**

In summary, most of the latest research on the topic is recommending to:

– use sparsely activated deep neural networks (see Figure 9) for energy savings,
– pay attention to the geographic location of the servers where ML workload runs,
– use of specialized infrastructure that includes accelerators appropriate for the task,
– duly report the energy consumption and CO2 emissions on machine learning papers and research, especially when it involves large training of models,
– use also efficiency as an evaluation metric (e.g., floating point operations), in combination with accuracy and other similar metrics,
– include the full training lifecycle in the calculations, which consider previous attempts needed until everything is set up correctly,
– take energy needs for inference into account, as these can often outweigh the training ones, and
– release pre-trained models to save others the cost of retraining them.

This list is non exhaustive but should serve as an indication of the state of play at the time of writing. There are also experts that are urging policy makers to stimulate transparency and the creation of standards, to facilitate the emission calculations in the area of artificial intelligence [b-Dhar].

## 9 Appliance of energy criteria to the end-to-end considered by this report

The energy efficiency good practices (introduced in clause 8) are applied to the three end-to-end application typologies introduced in clause 7, acknowledging the different components and the three main steps of the circular value-chain discussed.

## 9.1 Monitoring application using smart IoT systems and AI software

In the case of developing and managing monitoring applications by using smart IoT systems and AI software, good practices for energy efficiency are summarized in Table 1.

**Table 1 – Energy efficiency good practices for implementing monitoring application using smart IoT systems and AI software**

| Component | Value-chain step to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| **IoT systems** | Data storage | One or more of the following techniques:<br>• storage tiers<br>• storage virtualization<br>• thin provisioning<br>• data compression<br>• deduplication<br>• decommissioning of non-used storage<br>• snapshot technology | See clause 8.2 |
| | Data transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario identification<br>• threshold determination<br>• time-span determination<br>• execution strategy<br>• feedback and optimization | See clause 8.3.1 (for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |
| **Smart gateways** | Data transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario identification<br>• threshold determination<br>• time-span determination<br>• execution strategy<br>• feedback and optimization | See clause 8.3.1 (for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |
| | Data processing (ML) | One or more of the following techniques/strategies:<br>• hardware-based full stack optimization<br>• a "once-for-all" AI network (which trains a large model that has many pre-trained sub-models) – notably:<br>• use sparsely activated Deep Neural Networks for energy savings,<br>• pay attention to the geographic location of the servers where ML workload runs,<br>• use of specialized infrastructure that includes accelerators appropriate for the task,<br>• duly report the energy consumption and CO2 emissions on Machine Learning papers and research – specially when it involves large training of models;<br>• use also efficiency as an evaluation metric (e.g., floating point operations), in | See clause 8.4.2 |

**Table 1 – Energy efficiency good practices for implementing monitoring application using smart IoT systems and AI software**

| Component | Value-chain step to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| | | combination with accuracy and other similar metrics;<br>• include the full training lifecycle in the calculations, which considers previous attempts needed until everything is set up correctly,<br>• keep energy needs for inference into account, as these can often outweigh the training ones, and<br>• release pre-trained models to save others the cost of retraining them. | |
| **Smart services/Cloud** | Data storage | One or more of the following techniques:<br>• storage tiers<br>• storage virtualization<br>• thin provisioning<br>• data compression<br>• deduplication<br>• decommissioning of non-used storage<br>• snapshot technology | See clause 8.2 |
| | Data transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario identification<br>• threshold determination<br>• time-span determination<br>• execution strategy<br>• feedback and optimization | See clause 8.3.1 (for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |
| | Data processing (ML) | One or more of the following techniques/strategies:<br>• hardware-based full stack optimization<br>• a "once-for-all" AI network (which trains a large model that has many pre-trained sub-models) – notably:<br>• use sparsely activated deep neural networks for energy savings,<br>• pay attention to the geographic location of the servers where ML workload runs,<br>• use of specialized infrastructure that includes accelerators appropriate for the task,<br>• duly report the energy consumption and $CO_2$ emissions on machine learning papers and research – especially when it involves large training of models;<br>• use also efficiency as an evaluation metric (e.g., floating point operations), in | See clause 8.4.2 |

**Table 1 – Energy efficiency good practices for implementing monitoring application using smart IoT systems and AI software**

| Component | Value-chain step to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| | | combination with accuracy and other similar metrics;<br>• include the full training lifecycle in the calculations, which considers previous attempts needed until everything is set up correctly,<br>• keep energy needs for inference into account, as these can often outweigh the training ones, and<br>• release pre-trained models to save others the cost of retraining them. | |

### 9.2 Smart application using edge computing and Cloud data centre

In the case of developing and managing smart applications building on edge computing and Cloud data centre, good practices for energy efficiency are summarized in Table 2.

**Table 2 – Energy efficiency good practices for implementing smart application using edge computing and Cloud data centre**

| Component | Value-chain steps to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| **IoT systems** | Data storage | One or more of the following techniques:<br>• storage tiers<br>• storage virtualization<br>• thin provisioning<br>• data compression<br>• deduplication<br>• decommissioning of non-used storage<br>• snapshot technology | See clause 8.2 |
| | Data transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario identification<br>• threshold determination<br>• time-span determination<br>• execution strategy<br>• feedback and optimization | See clause 8.3.1 (for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |

**Table 2 – Energy efficiency good practices for implementing smart application using edge computing and Cloud data centre**

| Component | Value-chain steps to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| Smart gateways | Data transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario identification<br>• threshold determination<br>• time-span determination<br>• execution strategy<br>• feedback and optimization | See clause 8.3.1 (for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |
| | Data processing (ML) | One or more of the following techniques/strategies:<br>• hardware-based full stack optimization<br>• a "once-for-all" AI network (which trains a large model that has many pre-trained sub-models) – notably:<br>• use sparsely activated Deep Neural Networks for energy savings,<br>• pay attention to the geographic location of the servers where ML workload runs,<br>• use of specialized infrastructure that includes accelerators appropriate for the task,<br>• duly report the energy consumption and CO2 emissions on Machine Learning papers and research – especially when it involves large training of models;<br>• use also efficiency as an evaluation metric (e.g., floating point operations), in combination with accuracy and other similar metrics;<br>• include the full training lifecycle in the calculations, which considers previous attempts needed until everything is set up correctly,<br>• keep energy needs for inference into account, as these can often outweigh the training ones, and<br>• release pre-trained models to save others the cost of retraining them. | See clause 8.4.2 |
| Smart systems (Edge/Fog computing nodes) | Data storage | One or more of the following techniques:<br>• storage tiers<br>• storage virtualization<br>• thin provisioning<br>• data compression<br>• deduplication<br>• decommissioning of non-used storage<br>• snapshot technology | See clause 8.2 |

**Table 2 – Energy efficiency good practices for implementing smart application using edge computing and Cloud data centre**

| Component | Value-chain steps to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| | Data Transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario identification<br>• threshold determination<br>• time-span determination<br>• execution strategy<br>• feedback and optimization | See clause 8.3.1 (for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |
| | Data processing (ML) | One or more of the following techniques/strategies:<br>• hardware-based full stack optimization<br>• a "once-for-all" AI network (which trains a large model that has many pre-trained sub-models) – notably:<br>• use sparsely activated Deep Neural Networks for energy savings,<br>• pay attention to the geographic location of the servers where ML workload runs,<br>• use of specialized infrastructure that includes accelerators appropriate for the task,<br>• duly report the energy consumption and CO2 emissions on Machine Learning papers and research – especially when it involves large training of models;<br>• use also efficiency as an evaluation metric (e.g., floating point operations), in combination with accuracy and other similar metrics;<br>• include the full training lifecycle in the calculations, which considers previous attempts needed until everything is set up correctly,<br>• keep energy needs for inference into account, as these can often outweigh the training ones, and<br>• release pre-trained models to save others the cost of retraining them. | See clause 8.4.2 |
| **Smart services/Cloud** | Data storage | One or more of the following techniques:<br>• storage tiers<br>• storage virtualization<br>• thin provisioning<br>• data compression<br>• deduplication<br>• decommissioning of non-used storage<br>• snapshot technology | See clause 8.2 |

**Table 2 – Energy efficiency good practices for implementing smart application using edge computing and Cloud data centre**

| Component | Value-chain steps to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| | Data Transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario identification<br>• threshold determination<br>• time-span determination<br>• execution strategy<br>• feedback and optimization | See clause 8.3.1 (for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |
| | Data processing (ML) | One or more of the following techniques/strategies:<br>• hardware-based full stack optimization<br>• a "once-for-all" AI network (which trains a large model that has many pre-trained sub-models) – notably:<br>• use sparsely activated Deep Neural Networks for energy savings,<br>• pay attention to the geographic location of the servers where ML workload runs,<br>• use of specialized infrastructure that includes accelerators appropriate for the task,<br>• duly report the energy consumption and $CO_2$ emissions on Machine Learning papers and research – especially when it involves large training of models;<br>• use also efficiency as an evaluation metric (e.g., floating point operations), in combination with accuracy and other similar metrics;<br>• include the full training lifecycle in the calculations, which considers previous attempts needed until everything is set up correctly,<br>• keep energy needs for inference into account, as these can often outweigh the training ones, and<br>• release pre-trained models to save others the cost of retraining them. | See clause 8.4.2 |

## 9.3 Simulation applications using digital twin pattern

In the case of developing and managing simulation applications by applying the Digital Twin pattern, ]good practices for energy efficiency are summarized in Table 3.

**Table 3 – Energy efficiency good practices for implementing simulation applications applying the Digital Twin pattern**

| Component | Value-chain steps to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| **IoT systems** | Data storage | One or more of the following techniques:<br>• storage tiers<br>• storage virtualization<br>• thin provisioning<br>• data compression<br>• deduplication<br>• decommissioning of non-used storage<br>• snapshot technology | See clause 8.2 |
| | Data transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario identification<br>• threshold determination<br>• time-span determination<br>• execution strategy<br>• feedback and optimization | See clause 8.3.1 (for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |
| **Smart gateways** | Data transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario identification<br>• threshold determination<br>• time-span determination<br>• execution strategy<br>• feedback and optimization | See clause 8.3.1 (for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |
| | Data processing (ML) | One or more of the following techniques/strategies:<br>• hardware-based full stack optimization<br>• a "once-for-all" AI network (which trains a large model that has many pre-trained sub-models) – notably:<br>• use sparsely activated deep neural networks for energy savings,<br>• pay attention to the geographic location of the servers where ML workload runs,<br>• use of specialized infrastructure that includes accelerators appropriate for the task,<br>• duly report the energy consumption and CO2 emissions on Machine Learning papers and research – especially when it involves large training of models;<br>• use also efficiency as an evaluation metric (e.g., floating point operations), in combination with accuracy and other similar metrics; | See clause 8.4.2 |

**Table 3 – Energy efficiency good practices for implementing simulation applications applying the Digital Twin pattern**

| Component | Value-chain steps to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| | | • include the full training lifecycle in the calculations, which considers previous attempts needed until everything is set up correctly,<br>• keep energy needs for inference into account, as these can often outweigh the training ones, and<br>• release pre-trained models to save others the cost of retraining them. | |
| **Smart Systems (Edge/Fog Computing nodes)** | Data storage | One or more of the following techniques:<br>• storage tiers<br>• storage virtualization<br>• thin provisioning<br>• data compression<br>• deduplication<br>• decommissioning of non-used storage<br>• snapshot technology | See clause 8.2 |
| | Data transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario identification<br>• threshold determination<br>• time-span determination<br>• execution strategy<br>• feedback and optimization | See clause 8.3.1<br>(for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |
| | Data processing (ML) | One or more of the following techniques/strategies:<br>• hardware-based full stack optimization<br>• a "once-for-all" AI network (which trains a large model that has many pre-trained sub-models) – notably:<br>• use sparsely activated Deep Neural Networks for energy savings,<br>• pay attention to the geographic location of the servers where ML workload runs,<br>• use of specialized infrastructure that includes accelerators appropriate for the task,<br>• duly report the energy consumption and CO2 emissions on Machine Learning papers and research – specially when it involves large training of models;<br>• use also efficiency as an evaluation metric (e.g., floating point operations), in combination with accuracy and other similar metrics; | See clause 8.4.2 |

**Table 3 – Energy efficiency good practices for implementing simulation applications applying the Digital Twin pattern**

| Component | Value-chain steps to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| | | • include the full training lifecycle in the calculations, which considers previous attempts needed until everything is set up correctly,<br>• keep energy needs for inference into account, as these can often outweigh the training ones, and<br>• release pre-trained models to save others the cost of retraining them. | |
| **Smart services/Cloud** | Data storage | One or more of the following techniques:<br>• storage tiers<br>• storage virtualization<br>• thin provisioning<br>• data compression<br>• deduplication<br>• decommissioning of non-used storage<br>• snapshot technology | See clause 8.2 |
| | Data transfer (5G) | Implement the AI-driven smart procedure consisting of the steps:<br>• scenario Identification<br>• threshold Determination<br>• time-span Determination<br>• execution Strategy<br>• feedback and Optimization | See clause 8.3.1<br>(for Optical and copper networks, see clauses 8.3.2 and 8.3.3, respectively) |
| | Data processing (ML) | One or more of the following techniques/strategies:<br>• hardware-based full stack optimization<br>• a "once-for-all" AI network (which trains a large model that has many pre-trained sub-models) – notably:<br>• use sparsely activated deep neural networks for energy savings,<br>• pay attention to the geographic location of the servers where ML workload runs,<br>• use of specialized infrastructure that includes accelerators appropriate for the task,<br>• duly report the energy consumption and CO2 emissions on Machine Learning papers and research –specially when it involves large training of models;<br>• use also efficiency as an evaluation metric (e.g., floating point operations), in combination with accuracy and other similar metrics; | See clause 8.4.2 |

**Table 3 – Energy efficiency good practices for implementing simulation applications applying the Digital Twin pattern**

| Component | Value-chain steps to which it contributes | Energy efficiency good practices | Notes |
|---|---|---|---|
| | | • include the full training lifecycle in the calculations, which considers previous attempts needed until everything is set up correctly,<br>• keep energy needs for inference into account, as these can often outweigh the training ones, and<br>• release pre-trained models to save others the cost of retraining them. | |

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