Grant Agreement N° 872592

PLATOON
Digital platform and analytic tools for energy

Deliverable D8.1
Impact assessment of big data and advanced analytics for energy services

Contractual delivery date:
M12
Actual delivery date:
30th December 2020

Responsible partner:
P01: ENGIE, France

Project Title	PLATOON – Digital platform and analytic tools for energy
Deliverable number	D8.2
Deliverable title	Market and stakeholder analysis
Author(s):	Cs, ENGIE, ENGINEERING, MINSAIT, PUPIN, TECNALIA, VEOLIA
Responsible Partner:	P01 - ENGIE
Date:	30.12.2020
Nature	R
Distribution level (CO, PU):	PU
Work package number	WP8 – Business Models and Exploitation

Work package leader	IND
Abstract:	Digital transformation is having significant impact on the energy sector. The digital agenda in the energy sector is being driven by

	a combination of technologies, collection and use of data, and a more complex world demanding greater agility, speed, and digital competences. It is expected to impact all aspects of the energy sector, including changing patterns of consumption, new ways of optimizing assets, cross-industry partnerships, and the greater use of industrial platforms. Digital technologies and 'smart solutions' are being placed at the centre of new business models, and data is seen as an increasingly valuable asset. Therefore, T8.1 will focus on the opportunities to use big data, advanced analytics, and open data to solve problems faced by the energy sector today.
Keyword List:	Big data, digital platforms, impacts, energy sector, open data, Analytics tools.

The research leading to these results has received funding from the European Community's Horizon 2020 Work Programme (H2020) under grant agreement no 872592.

Editor(s):	Cs, ENGIE, ENGINEERING, MINSAIT, PUPIN, TECNALIA, VEOLIA
Contributor(s):	Cs, ENGIE, ENGINEERING, MINSAIT, PUPIN, TECNALIA, VEOLIA
Reviewer(s):	Pau Joan Cortés Forteza Philippe Calvez Erik Maqueda-Moro
Approved by:	Philippe Calvez (ENGIE) – PLATOON Coordinator Erik Maqueda (TECN) – Technical Coordinator First Name Eduardo Jimenez (IND) – Exploitation Coordinator
Recommended/mandatory readers:	Pau Joan Cortés Forteza Philippe Calvez Erik Maqueda-Moro

Document Description

Version	Date	Modifications Introduced	
		Modification Reason	Modified by
V0.1	04.11.2020	Section 1 – Introduction and Section 2 - Big Data challenges and opportunities in the energy sector	V. Janev
V0.2	16.11.2020	Section 2.2-2.8	J.Prieto Vivance, E.Jimènez Segado
V0.3	27.11.2020	Section 3. Potential Big data applications in the energy services	I.Matranga
V0.4	30.11.2020	Section 4 New business models	I.Matranga
V0.5	04.12.2020	Section-5: big data impact update	D.Carro
V0.6	04.12.2020	Section 6: PLATOON use cases and expected impacts	R.Pecqueur
V0.7	07.12.2020	Document consolidation	L.Bouchendouka
V0.8	08.12.2020	Conclusion and final details	L.Bouchendouka
V0.9	11.12.2020	Section 4 updates	I.Matranga
V0.10	12.12.2020	Final details, updates, and modifications	L.Bouchendouka
V0.10	14.12.2020	First review	P. Cortés Forteza
V0.10	21.12.2020	Second review	E.Maqueda-Moro
V1.0	29.12.2020	Corrections and final changes	L.Bouchendouka

Acknowledgements

The following people are hereby duly acknowledged for their considerable contributions, which have served as a basis for this deliverable:

Name	Partner
David CARRO SANTOME	Cs
Andrej Čampa	CS
Lilia BOUCHENDOUKA	ENGIE
Rémi PECQUEUR	ENGIE
Martino MAGGIO	ENGINEERING
Isabel MATRANGA	ENGINEERING
Prieto Vivanco, Juan	MINSAIT
Jiménez Segado, Eduardo	MINSAIT
Merino Blanco, Fernando	MINSAIT
Valentina JANEV	PUPIN
Maqueda Moro, Erik	TECNALIA
Gorka NAVERAN	VEOLIA

Executive Summary

This document lies under the scope of work package WP8- Business Models and Exploitation. Its content is based on the work of the Task 8.1 - Project Impact Assessment, led by ENGIE.

The deliverable D8.1-impact assessment of big data and advanced analytics for energy services- focuses on an important topic within the PLATOON project, the definition of opportunities using big data, advanced analytics, and open data to solve problems faced by the energy sector today. Those are an important element that will allow the project consortium to evaluate the impacts of the different services and functionalities to be provided by PLATOON platform as well as assumptions are.

The impact expected to be created within PLATOON is based on the synergistic effect of activities initiated in WP2 to WP6 framework, as is presented in Figure 1 below. Data integration activities in WP2 focuses on common data models and standardization through a technology-agnostic approach to be compliant with very different technologies. WP3 will deliver data governance, security and privacy framework along with open-source IDS components that will further improve the interoperability and sovereign data exchange between different energy sector stakeholders. Furthermore, WP3 will create the PLATOON marketplace, a one-stop shop where energy sector stakeholders can share data and tools maintaining security, privacy and sovereignty. Analytical components delivered in WP4 framework for batch and real-time processing will feature standard interfaces and easy integration with existing energy management systems. The developed prototype applications will be validated in seven large scale pilots, organised in 3 groups: 1) Predictive maintenance for wind-energy, 2) Smart grid management, 3) End use of the energy) will ensure that the PLATOON will make impact in all parts of the energy value chain.

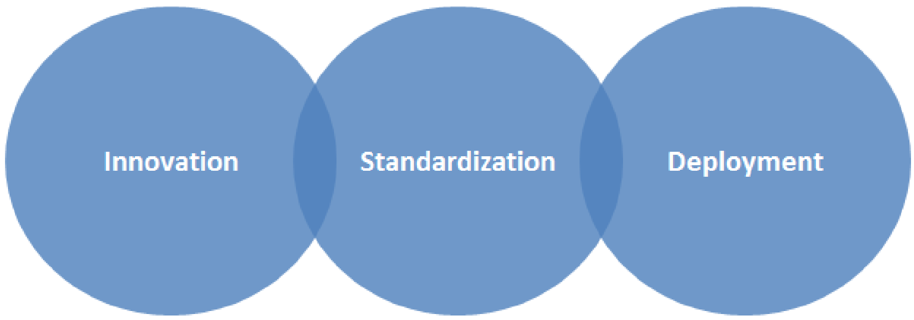


Figure 1 : From innovation, via standardization to deployment

Altogether, this impact assessment will be used in later project phases to ensure proper verification and validation of the PLATOON project.

Table of Contents

List of Figures

List of Tables

Terms and abbreviations

OT	Operational Technology
P2P	Peer-to-peer
IoT	Internet of thinks
AI	Artificial intelligence
ML	Machine Learning
DL	Deep Learning
IT	Information Systems
SG	Smart Grid
RES	Renewable Energy Sources
B2C	Business to consumer

1. Introduction

1.1 PLATOON project overview

Over the past years, the topics of Big Data[1], Linked Data[2] , Open Data[3] , and Smart Data[4] have spawned a tremendous amount of attention among scientists, software experts, industry leaders and decision makers. This amount of data that is created on daily bases creates new opportunities for modern enterprises, especially for using the latest advancements in analytics for analysing the industry value chains in a broader sense. The Energy Big Data framework of the modern smart energy networks provides an ideal ecosystem for Utilities´ data knowledge generation. Big Data provides the opportunity to better monitor, correct, and integrate smart grid technologies and renewable energy. At the same time, data management and utilization must be integrated into the organization's operations to maximize business value.
Hence, the ambition of PLATOON project is to deploy distributed/edge processing and data analytics technologies for optimized real-time energy system management in a simple way for the energy domain expert. The project will build upon European standards and initiatives for managing the pilots' data, for the access, models, interfaces, governance, and sovereignty. The data governance among the different stakeholders for multi-party data exchange, coordination and cooperation in the energy value chain will be guaranteed through IDS (Industrial Data Space)-based connectors. The project will develop and use the PLATOON reference architecture, COSMAG-compliant, for building and deploying scalable and replicable energy management solutions that contribute to increased renewable energy demand, smart grids management, increased energy efficiency and optimised energy asset management.

1.2 Objective and scope of the Impact assessment of big data and advanced analytics for energy services

In PLATOON WP8 (Business Models and Exploitation) framework, the Task 8.1 focuses on the opportunities of using big data, advanced analytics, and open data to solve problems faced by the energy sector today. Some of the **high-level impacts expected from deployment of PLATOON services** across Europe are as follows**:**

- Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains.
- Enhancing energy asset management, increasing consumer participation and innovative network management, creating new data-driven business models and opportunities and innovative energy services.
- Contribution to increasing the use of renewable energy and increased energy efficiency based on optimised energy asset management, offering access to cheaper and sustainable energy for energy consumers and maximising social welfare.

[1] D. Laney, Laney, D.: 3D data management: controlling data volume, velocity, and variety.Application Delivery Strategies, Meta Group (2001)
[2] Bizer, C., Heath, T., & Berners-Lee, T. (2009). Linked data – The story so far. In T. Heath, M. Hepp, M., & Bizer, C. (Eds.), *Special Issue on Linked Data, International Journal on Semantic Web and Information Systems, 5*(3), 1-22.
[3] Wided Medjroubi, Ulf Philipp Müller, Malte Scharf, Carsten Matke, David Kleinhans (2017) Open Data in Power Grid Modelling: New Approaches Towards Transparent Grid Models,
Energy Reports, Volume 3, Pages 14-21, https://doi.org/10.1016/j.egyr.2016.12.001.
[4] http://traces.cs.umass.edu/index.php/Smart/Smart

- Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes.
- Increased in standards for data sharing, exchange, and integration.

1.3 Relation to other deliverables

The impact expected to be created within PLATOON is based on the synergistic effect of activities initiated in WP2 to WP6 framework, as is presented in Figure 1 below. Data integration activities in WP2 focuses on common semantic data models and standardization through a technology-agnostic approach to be compliant with very different technologies. WP3 will deliver data governance, security, and privacy framework along with open-source IDS components that will further improve the interoperability and sovereign data exchange between different energy sector stakeholders. Furthermore, WP3 will create the PLATOON marketplace, a one-stop shop where energy sector stakeholders can share data and tools maintaining security, privacy, and sovereignty. Analytical components delivered in WP4 framework for batch and real-time processing will feature standard interfaces and easy integration with existing energy management systems. The developed prototype applications will be validated in seven large scale pilots, organised in 3 groups making impact in all parts of the energy value chain.:

1) Predictive maintenance for wind-energy,
2) Smart grid management,
3) End use of the energy

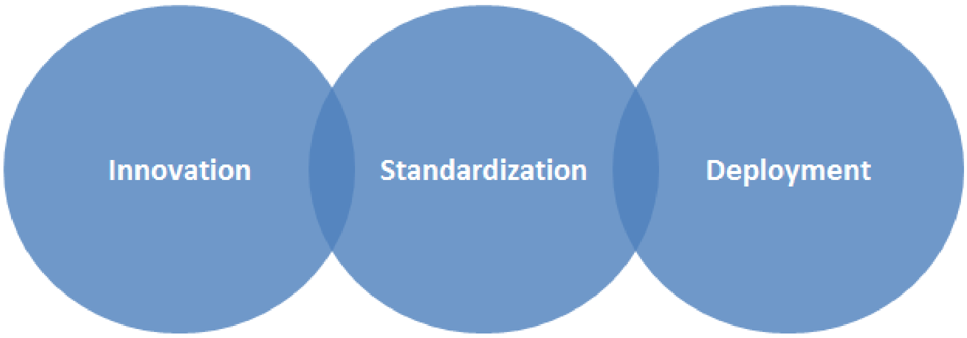


Figure 2 : From innovation, via standardization to deployment

2. Big Data challenges and opportunities in the energy sector

In the **energy sector,** the new paradigm of smart grids that includes renewable energy sources, storage, and efficiency from its broadest point of view, challenges the existing network infrastructure and legacy information systems (IT).

The management and use of data generated from the different components of the power system are critical to the successful implementation and operation of the system.

Here, the processes of energy generation, transmission, distribution, and demand must be concurrently monitored and analysed to assure system stability without brownouts or blackouts.

Modern transmission systems (grids) in developed countries that transport electricity are in general very large and robust infrastructures with extensive deployment of monitoring and control equipment. Novel Internet of Things (IoT) sensors and actuators are pushing this monitoring and control capabilities into the lower levels of the grid even into connected customers' homes.

Such reliability and extended monitoring and control capability is key to ensure the efficiency and stability of the power system, one of the most critical infrastructures in any country.

2.1 Big Data dimensions

The energy sector has been dealing with big data for decades, as tremendous amounts of data are collected from numerous sensors, which are generally attached to different plant subsystems on the production side or metering equipment and sensors that provide key insights into load distribution. However, the term "Big Data" became more popular and used also in energy sector discussions after the definition of Big Data (3Vs) create by Gartner group in 2001:

> Big data" is **high-volume**, **velocity**, and **variety** information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making[5].

Many different definitions have emerged over time[6], but in general, it refers to "datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyse"[7] and technologies that address "data management challenges" and process and analyse data to uncover valuable information that can benefit businesses and organizations. Additional "Vs" of data have been added over the years, see Table below.

Table 1. Big Data characteristics

[5]https://www.forbes.com/sites/gartnergroup/2013/03/27/gartners-big-data-definition-consists-of-three-parts-not-to-be-confused-with-three-vs/?sh=424b6c3142f6

[6] V. Janev, D. Graux, H. Jabeen, E. Sallinger (Eds.) Knowledge Graphs and Big Data Processing. Lecture Notes in Computer Science vol. 12072, pp. 1-208. Springer International Publishing. ISBN 978-3-030-53198-0. DOI: https://doi.org/10.1007/978-3-030-53199-7

[7] J. Manyika. Big data: The next frontier for innovation, competition, and productivity.
The McKinsey Global Institute, pages 1|-137, 2011.

Volume	**Vast amount of data that must be captured, stored, processed, and displayed.**
Velocity	Rate at which the data is being generated or analysed.
Variety	Differences in data structure (format) or differences in data sources themselves (text, images, voice, geospatial data).
Veracity	Truthfulness (uncertainty) of data, authenticity, provenance, Accountability.
Validity	Suitability of the selected dataset for a given application, accuracy, and correctness of the data for its intended use.
Volatility	Temporal validity and fluency of the data, data currency and availability, and ensures rapid retrieval of information as required.
Value	Usefulness and relevance of the extracted data in making decisions and capacity in turning information into action.
Visualization	Data representation and understandability of methods (data clustering or using tree maps, sunbursts, parallel coordinates, circular network diagrams, or cone trees).
Vulnerability	Security and privacy concerns associated with data processing.
Variability	The changing meaning of data, inconsistencies in the data, biases, ambiguities, and noise in data.

Big data in the energy domain (even greater now with the introduction of smart grids) are heterogeneous, with varying resolution, mostly asynchronous, and are stored in different formats (raw or processed) at various locations. For example, typical smart meter data are energy demand collected every 15 minutes and are stored in billing centres. One million smart meters installed in a utility results to nearly 3 TB of new energy demand data every year[8].

[8] Big Data Analytics in Smart Grids: State-of-the-Art, Challenges, Opportunities, and Future Directions. IET Generation, Transmission and Distribution · February 2019

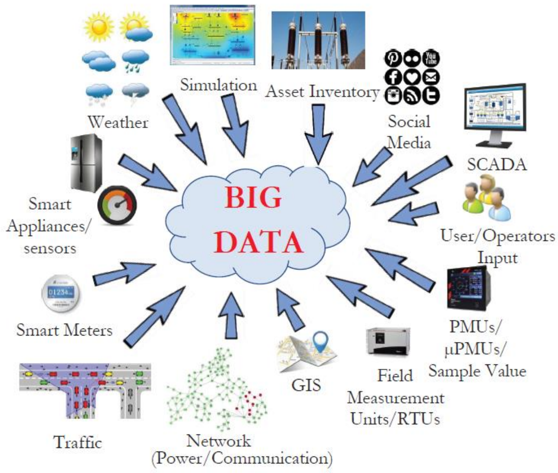


Figure 3 Sources of non-electrical big dataset in smart grids

These big data carry considerable amount of information that enables novel Data Driven control algorithms. This in turn can bring revolutionary transformations to the way grids are planned and operated. Big data in the energy sector allows improvisation in existing operation and planning practices at all levels, i.e., generation, transmission, distribution, and end users[9]. The key challenge of big data analytics is to turn large volume of raw data into actionable information by effectively integrating into power system operational decision frameworks[10].

2.2 Data value generation: distributed data value.

Power systems are currently managed using central data processing architectures and technologies.

Based on this centralizing approach the increasing need for broader and deeper sensing and control of the generation and grid assets is increasing at an exponential rate the **volume** of data over which utilities need to gain insights and react at an increasing **velocity** to generate **value** thus fully plunging utilities in the **Big Data**.

When faced with thousands, if not millions, of measurement and control points as it would be the case of power grids (down to Low voltage), current centralized data processing approach starts losing efficiency and facing serious limitations:

- More than 80% of the information sent for central processing has little, if any value, but cannot be directly discarded until processed.
- Communications are used to their limit, and available bandwidth consumed with data that may not be valuable.
- Cost for central processing and data processing increases exponentially.
- Reaction times to all this massive influx of data is continually increasing, thus limiting the value of Big data.

The continuous lowering of the cost of industrial computing equipment and the deployment of new distributed IoT/Edge architectures provides, in a unique manner, answers to the Big Data Challenge posed to Power companies.

These impacts and benefits of distributed big data mirror those of distributed generation in the power system, creating bottlenecks and loss of efficiency when centrally managed and

[9] K. Zhou, C. Fu, and S. Yang, “Big data driven smart energy management: From big data to big insights,” Renewable and Sustainable Energy Reviews, vol. 56, pp. 215–225, 2016

[10] J. Hu and A. V. Vasilakos, “Energy big data analytics and security: challenges and opportunities,” IEEE Transactions on Smart Grid, vol. 7, no. 5, pp. 2423–2436, Sep. 2016

increasing flexibility, reliability, efficiency, and capacity when the management architecture mimics its distributed nature.
The combination of Central & Cloud computing with distributed Fog & Edge computing, if correctly coordinated, creates a hybrid central/distributed architecture where:

1. **Big data is processed incrementally in layers from the source**, ensuring that only valuable data is exploited.
2. **Data intelligence is optimally distributed along the data chain**. Analytics is placed at the closest point to the asset or the system over which value needs to be generated, thus simplifying the access to relevant data, and maximizing reaction times.
3. **Communication data processing and storage is optimized** as only relevant data with maximum value and minimum volume needs to be managed.

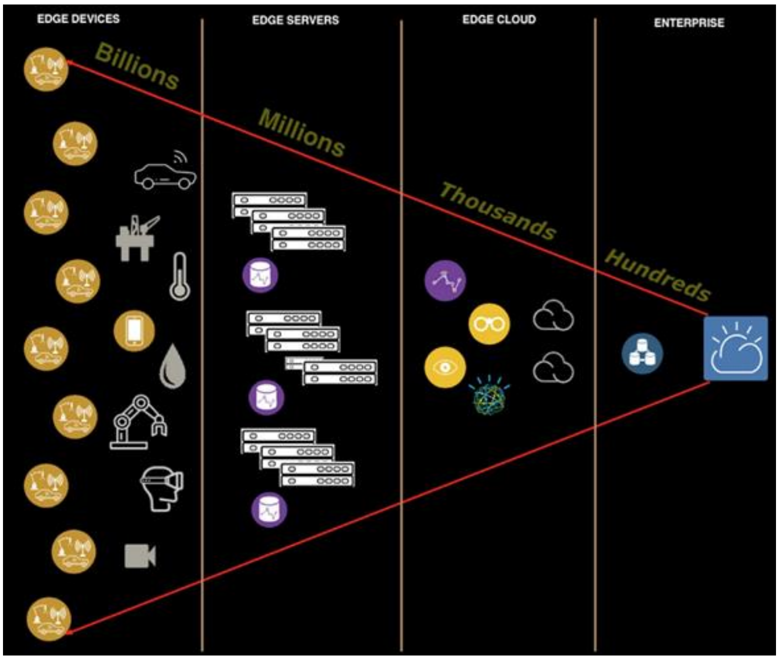


Figure 4 Big Data funnel in a hybrid Cloud/Edge distributed architecture

2.3 The challenge of data value encapsulation and interoperability.

The ambition of PLATOON project is to deploy distributed/edge processing and data analytics technologies to optimize the operation of the real-time energy system management.
To achieve this target is key to define a standard framework to encapsulate, communicate and manage in a distributed architecture different data analytic module thus increasing the efficiency and reliability of renewable generation resources, the grid and demand.
The moment that assets are managed through "networks" of distributed analytics that could involve hundreds if not thousands of data Analytic agents in coordination, a distributed architecture should standardize the way those analytics are encapsulated, communicated, managed, and distributed.
Virtualization (Virtual machines, containers of serverless functions) is the leading strategy in the IoT domain, that PLATOON will apply to allow this encapsulation of analytic functions in the power domain.

Even though there are a few standard information models for smart grid interoperability (e.g., IEC 61850, IEC 61850-90-7, IEC 61970/61968, IEEE 1815, IEEE 2030.5), there is no standard information models to describe interoperability among various big data analytics platforms, architecture, and their operational integrations with utility decision frameworks. Furthermore, storage, usage, dissemination, and sharing of data with utility operational frameworks are not unified. Interoperability between various cloud computing service vendors is necessary. Therefore, extensive R&D is needed to develop interoperability among different devices, network operations, data analytics platforms, big data architecture, data repository, and information models.

2.4 PLATOON use cases and data categorization

While companies in the past used to process static data, centrally stored, and collected from various sources, with the birth of the web and cloud services, cloud computing is rapidly overtaking the traditional in-house system as a reliable, scalable and cost-effective IT solution. The high volumes of structured and unstructured data stored in a distributed manner, and the wide variety of data sources pose problems related to data/knowledge representation and integration, data querying, and business analysis. To specify the needs of PLATOON Pilot applications (delivered in WP6 framework), in the project preparation phase, the available datasets were analysed and categorized in accordance with the 3Vs (Volume, Variety and Volume). For more information about the data sources and integration, please check deliverable D2.4.

2.5 PLATOON use cases and Big Data Analytics -Challenges and Opportunities

2.6 Standardization

In the report published by CEN-CENELEC-ETSI Coordination Group on Smart Energy Grids (CG-SEG) in January 2017[11], reference standards for smart energy grids are listed for the domain of advanced Distribution grid operation systems.

PLATOON solutions would have to comply with this list of standards mainly focused in the interoperability between sensors, controls and systems

Layer	Standard	Comments
	IEC 61869	Measurement transformers & sensors
	IEC 62271 series	High-voltage switchgear and control gear
Communications	IEC 61968-100	Application integration at electric utilities - System interfaces for distribution management - Part 100: Implementation profiles
Communications	IEC 62351 (all parts)	Cyber-security aspects (refer to section 9.4)
Communications & information	EN 61970 (all parts)	Some issues will be relevant of this family of standards but focus on this family of standards is on transmission
Communications & information	IEC/EN 61850 (all parts)	
Communications	IEC 60870-5-101	Remote control
Communications	IEC 60870-5-102	Measure

[11] SEGCG/M490/G_Smart Grid Set of Standards Version 4.1, 06/01/2017

Communications	IEC 60870-5-103	Protection and control
Communications	IEC 60870-5-104	Remote control
Communications	IEC 61158 series	Field buses
Communications	IEC 61400-25	Wind farms
Communications	IEC 61588 (IEEE 1588)	Time synchronization (PTP)
Communications	IEC 62056-5-3	DLMS / COSEM
Communications	IEC 62351 series	Cybersecurity
Communications	IEC 62361 series	Data Models (CIM)
Communications	IEC 62488-1 (Formerly EN60663) - Part 1	PLC
Communications	IEEE 1901	Broadband PLC
Communications	ISO/IEC 12139-1	MAC layer
Communications	ISO/IEC 14908	Network control
Communications	ISO/IEC 15118	V2G
Communications	ISO/IEC 15802 IEEE 802.1	Data exchange between systems
Communications	ISO/IEC 7498-1	OSI reference model
Communications	ISO/IEC 8802-3	Data exchange between systems
Communications	ITU-T G.7042	Link capacity tuning scheme for virtual concatenated signals
Communications	ITU-T G.707	Network node interface for synchronous digital hierarchy
Communications	ITU-T G.709	Interfaces for the optical transport network
Communications	ITU-T G.783	Characteristics of the functional blocks of the synchronous digital hierarchy equipment
Communications	ITU-T G.798	Characteristics of the functional blocks of the optical transport network hierarchy equipment
Communications	ITU-T G.803	Architecture of transport networks based on the synchronous digital hierarchy
Communications	ITU-T G.872	Architecture of optical transport networks
Communications	ITU-T G.983.1	Broadband optical access systems based on passive optical networks
Communications	ITU-T G.983.2	control and management interface of optical network terminals for passive broadband optical networks
EMC	IEC 61000 Series	EMC, Environmental, Mechanical
EMC	IEC 61326	Electrical material for measurement, control and laboratory use.
General	EN 61968-1	Application integration at electric utilities - System interfaces for distribution management - Part 1: Interface architecture and general requirements

General	IEC 62357	Reference architecture power system information exchange
General	ISO/IEC 27001	Information security
General	ISO/IEC 27002	Information security
Information	EN 61968-11	Application integration at electric utilities - System interfaces for distribution management - Part 11: Common information model (CIM) extensions for distribution
Information	EN 61968-13	Application integration at electric utilities - System interfaces for distribution management - Part 13: CIM RDF Model exchange format for distribution
Information	EN 61968-2	Application integration at electric utilities - System interfaces for distribution management - Part 2: Glossary
Information	EN 61968-3	Application integration at electric utilities - System interfaces for distribution management - Part 3: Interface for network operations
Information	EN 61968-4	Application integration at electric utilities - System interfaces for distribution management - Part 4: Interfaces for records and asset management
Information	EN 61968-6	Application integration at electric utilities - System interfaces for distribution management - Part 6: Interfaces for maintenance and construction
Information	EN 61968-8	Application integration at electric utilities - System interfaces for distribution management - Part 8: Interface Standard For Customer Support
Information	EN 61968-9	Application integration at electric utilities - System interfaces for distribution management - Part 9: Interfaces for meter reading and control
Information	IEC 62361-100	CIM profiles to XML schema mapping

Table 1 reference standards for smart energy grids

The previous list of standards focused on smart grid control systems is completed with a set of cybersecurity standards, evolved from existing industrial cybersecurity standards.

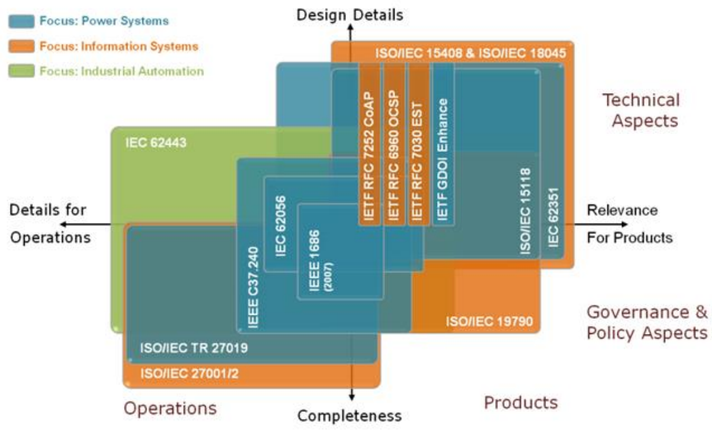


Figure 3: Cybersecurity standards : CEN-**CENELEC-ETSI Smart Grid Coordination Group (2014)**

Among the most notable for its orientation to Smart Grid or international presence are the following:

- IEC 62351
- IEEE 1686
- IEC 62443
- IEC 27019 - ISO/IEC 27001
- NISTIR 7628 Guidelines for Smart Grid Cyber Security
- NERC CIP: Critical Infrastructure Protection
- Common Criteria (ISO/IEC 15408)
- CEN/CENELEC/ETSI: Smart Grid Information Security

All of them have common points, some being more general and others being more focused on devices, operations, design, or processes.

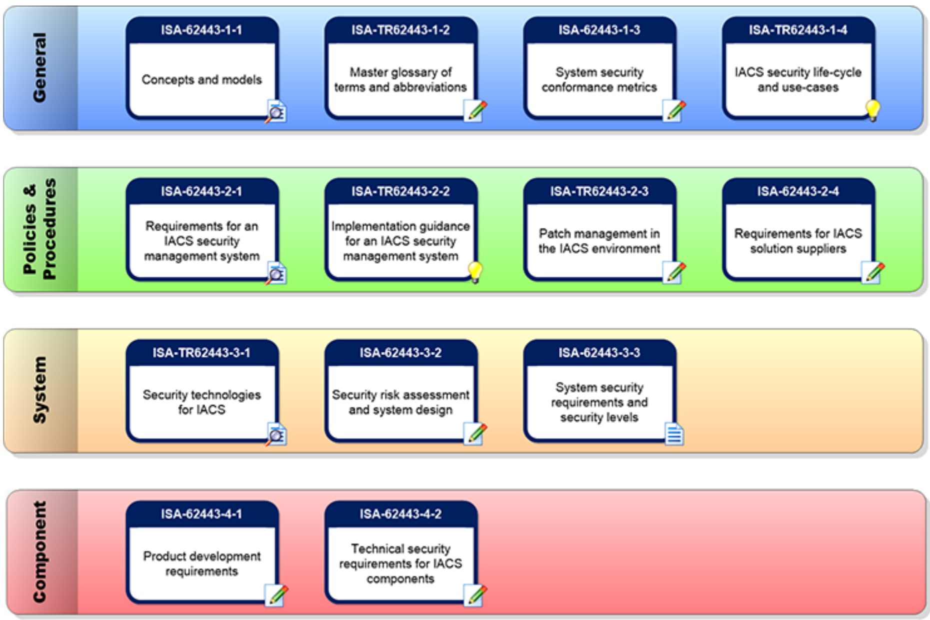


Figure 5 Smart grid standards categories

Many of the mentioned standards cover most of the aspects that can be found from the device to the Edge, central control centres and the cloud as in the case of IEC62351 and IEEE1686 or section 4 of IEC62443.
IEC62443 however, also covers aspects related to the union of the OT (Operational technology) world with IT (information technology), establishing cybersecurity practices that could be extrapolated to the Cloud.

2.7 Barriers to the implementation of Big Data in the Energy domain

The systems in the electricity sector need to improve in many aspects, one of them would be an internal problem of the company itself and is the collection of the data and the processing thereof. In many cases, they lack all the data (or at least many of them) recorded by the smart meters, thus making the task of data processing and analysis difficult. This translates to administrative errors on the part of the company.
A normative and legal reform in the Electricity Sector would also be necessary, especially the use of meters would allow to improve the integration of renewable energies for end users who have solar panels, allowing in addition to the generation of their own electricity, a control of the same by registering the data, as well as the visualization of the energy generated during demand peaks.
The business of electric companies is to sell energy and there is a direct relationship between the energy they sell and their profits. Therefore, it is difficult for a power utility to decide to promote energy efficiency that will reduce demand or flexibility services that will optimize the use of existing infrastructure thus reducing grid investment.
To overcome this obstacle new policies are required to incentivize Power Utilities to digitalize their infrastructure and enable a more active participation of grid users (generation and demand) in the power system operation.
The implementation of intelligent automatic systems enables Utilities to extend their real-time knowledge and control to lower and lower levels in the grid. As mentioned in previous sections the massive amount of data potentially actionable and the need to understand and respond very fast to this massive data is proving to be a very significant obstacle in current centralized architectures and a challenge to bid Data technologies.
Finally, a large initial investment is required in new infrastructures (sensors, smarter systems, more powerful and faster processors) will make many companies rethink their implementation.
This general challenges in the power sector poses at the following specific barriers that the exploitation of PLATOON technologies will have to solve to materialize the impacts identified:

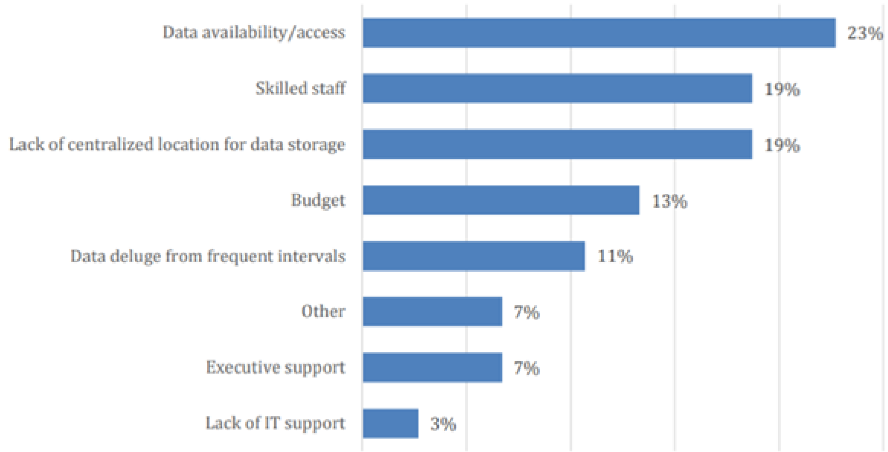
- Skills:
    - There are comparatively few people who can apply big data management and analytics knowledge together with domain know-how within the sectors.
- Interpretation:
    - Implicit or tacit models are in the heads of the (retiring) skilled workers. Scalable domain model extraction becomes key, e.g., in traffic management systems rule bases grow over years to unmanageable complexities.
- Digitization has not yet reached the tipping point:
    - Digitization and automation of infrastructure require upfront investments, which are not well considered, if at all, by the incentive regulation by which

    infrastructure operators are bound. Real-time higher-resolution data is still not widely available.

- Uncertainty regarding digital rights and data protection laws:
    - Unclear views on data ownership hold back big data in the end user facing segments of the energy and transport sectors (e.g., smart metering infrastructure).
- "Digitally divided" European union:
    - Europe has fragmented jurisdiction when it comes to digital rights.
- "Business-as-usual" trumps "data-driven business":
    - In established businesses it is very hard to change running business value chains. Incumbents will need to deal with a lot of changes: change in the existing long innovation cycles, change to walled garden views of closed systems and silos, and a change in the mind-set so that ICT becomes an enabler if not a core competency in their companies.
- Missing end user acceptance:
    - In the energy sector it is often argued that people undervalue the potential of energy usage data. However, when missing end user acceptance of a technology is argued, it is more a statement that a useful service using this technology is not yet deployed.
- Missing trust:
    - Trust is an issue that could and should be remedied with technology data protection and with regulatory framework (i.e., appropriate privacy protection laws)[12].

In the following figure you can see which are the major obstacles to the implementation of analytics in the energy sector.
Topping the list is data availability / access (23%), closely followed by qualified staff and the lack of a centralized location for data storage, which were identified as a top challenge by 19% of respondents. Only 13% considered budgeting the number one challenge for their current analytics projects. Together, these findings indicate that the biggest hurdles for 60% of the market can be traced back to the current state of the data itself and the dearth of people who know what to do with it.

[12] Rusitschka, S., and Curry, E. 2016. Big data in the energy and transport sectors. In *New Horizons for a Data-Driven Economy*, pp. 225-244. Springer, Cham.



.

Figure 6 Top analytics Challenges [13]

In the following table you can see how the project addresses each of these obstacles to facilitate the introduction of analytical techniques in the energy sector (How PLATOON responds to these barriers).

BARRIERS	PLATOON ANSWERS
Data availability/access	Open API and adoption of common data models in the domain of Energy and Big Data. PLATOON will build a Data Governance component based on IDS which ensures that the data is shared and utilized according to the specific agreements signed by the different stakeholders
Skilled staff	Data Analytics toolbox provides modular and accessible solutions to the energy domain expert in an easy way and to be used in solving their different problems.
Lack of centralized location for data storage	Thorough an interoperability layer based on open APIs and open data models based on existing standards that will enable the effective communication amongst different platforms.
Budget	Using Open-source platforms and systems like FIWARE and SANSA or open-source CKAN extensions providing a data portal with monetization capabilities
Data deluge from frequent intervals	Development of hybrid models from physical models of equipment and calibrated through error minimization techniques with operational data towards the digital twin.
Executive support	Through the dissemination activities of the project where the benefits that the proposed architecture can provide to their businesses will be explained in detail, for example a marketplace of additional services to their usual businesses.
Lack of IT support	Promoting software as a service it is no needed to install and maintain it locally.

Table 2 PLATOON vs Analytical Challenges

[13] The Current State of Smart Grid Analytics. Utility Analytics Institute.2017

2.8 Business in the energy sector

The following section examines the dimensions of big data in energy to identify the needs of businesses and end users with respect to big data technologies and their use.

The data from the energy sector come from high and medium voltage substations, although it is expected that in a very short time an avalanche of information from the new digitization of secondary substations, in a network infrastructure where distribution and marketing have been separated (unbundled)

The information can come in the form of service reports of maintenance work performed by field personnel, asset monitoring sensors, measurement and control devices, smart meters (readings and alarms), and high-resolution real-time data from phasor measurement units synchronized with GPS, etc.

The estimated annual data volume would be 1.8 billion records or 120 TB of raw data. A second wave will include granular data from smart appliances, electric vehicles, and other measurement points across the network. That exponentially increases the amount of data that is generated [14].

This massive volume of raw data will need to be analysed and filtered in real time to identify potential threads to the power system reliability or efficiency, generating control actions in time horizons ranging from 1 ms to 1 minute.

Energy flexibility and efficiency services needs to be agreed and dispatched in ranges from 1 second to hours.

Incumbent OT are unable to manage these massive data volumes creating a market that is expected to grow more than 75% over the next years.

3. Potential Big data applications in the energy services

The innovations brought by big data are changing the landscape of traditional energy industry and are going to support in addressing several challenges the energy sector is facing nowadays as for example: managing operational efficiency and cost control, providing system stability and reliability, manage renewable energy, improve energy efficiency to tackle environmental issues, improve consumer services.

One of the main examples of big data application is in the sector of smart grids which produce an enormous amount and various types of data (e.g., data on electricity demand or on device status). In this environment big data analytics can provide effective and efficient decision support for all the stakeholders involved from the producers, to the operators, from the customers to the regulators.

[14] B Laperche, F Picard, Environmental constraints, Product-Service Systems development and impacts on innovation management: learning from manufacturing firms in the French context, Journal of Cleaner Production, 2013

The application of data analysis techniques, as for example optimization, forecasting, classification, and clustering can in fact support:

- optimization of power generation and operation.
- integration of RES generation.
- prediction of electricity demand.
- discovery of electricity demand patterns.
- development of effective dynamic pricing mechanisms.
- detection of failures supporting prompt restore.

There have already been many successful application cases of big data analytics in the energy sector, one example is Google's DeepMind[15] technology which through the application of algorithms was able to increase the effectiveness of Google's customers' data centres' cooling systems by 30%. Other big players have also been working extensively in energy predictions by using machine learning and bid data. IBM for example has over 200 partners and clients that use their solar and wind forecasting technology. The technology integrates massive data sources and applies forecasting models to calibrate and improve efficiency and reliability[16]. Below we provide some of the main examples of application of big data in the energy sector.

Power generation and planning

Power generation planning and economic load dispatch can be considered as two of the most important decision-making processes in power generation. In simple terms, economic load dispatch is matching power supply with the demand for energy from the grid over a short period of time at the lowest possible cost subject to transmission and distribution constraints. Matching energy supply and demand on the network has always been a challenge. Through the application of different analytics techniques (e.g., prediction of electricity demand, discovery of demand patterns) to the enormous amount of data collected, power generation and planning can be optimized, energy production efficiency can be significantly improved, and the production costs can be greatly reduced.

Renewable energy management

Power generation and planning, seen above, become even more challenging when renewable energy is fed into the grid. The scarcity of fossil fuels and ecological transition are increasing the need and dependency on alternate sources of energy, such as solar and wind which are inevitably significantly affected by weather conditions. Feeding renewable energy into the power grid with incomplete information about individual power generation facilities can lead to volatility in load flow that is difficult to forecast. It has become imperative to use big data-based analytical tools, to understand the behaviour or adaption of these sources of energy; in fact, through massive weather data analysis forecasts the power generation can become more accurate and efficient. Furthermore, by merging various sources of data e.g., energy production and demand data with GIS data and weather data, renewable power generation devices can be selected more efficiently to improve power output and energy efficiency and overloads can be prevented at an early stage preventing costly re-dispatching.

[15] https://deepmind.com/

[16] Digitalisation of New Business Models in the Energy Secotr, University of Cambridge, June 2019

Demand side management

On the demand side management big data analytics can be applied for several purposes such as load forecasting, load classification and consumers segmentations, dynamic pricing and to apply demand response programmes. In a domain where the competition is strong an efficient demand side management can be considered as one of the means to improve loyalty and satisfaction of customers providing power companies the opportunity to maintain their market share and gain new ones. Existing systems such as Meter Data Management Systems, customer information systems, geographic information systems, and other data sources such as weather are analysed to offer targeted signals to Demand Response customers. Data analytics techniques can offer locational-based dispatch capabilities to the utilities and support the improvement of grid reliability.

Maintenance of machinery and equipment monitoring

Big data analytics can also play an important role in the maintenance of machinery and in the monitoring of equipment. Different approaches to machinery maintenance have been developed in the past years and data analytics today represents the opportunity for the energy sector to advance its procedures making them more efficient through predictive maintenance. Instead of waiting for a piece of equipment to fail (reactive maintenance) or perform regular maintenance checks (preventive maintenance) predictive maintenance enables the evaluation of the condition of the equipment by performing periodic or continuous (online) equipment condition monitoring. The goal of predictive maintenance is to perform maintenance at the time when the activity would be most cost-effective and before the equipment loses performance within a threshold. Effective predictive maintenance is only possible if it can leverage multi-sources of data coming from different systems e.g., Manufacturing Execution Systems, Building Management System, and the Energy Management System.

4. New business models

Digitalization in the energy sector is opening the way to the development of new business models. At the heart of disruption in business modelling in the energy sector is the use of technologies like blockchain, big data and analytics and the development of the P2P energy sharing concept. P2P is a novel paradigm of power system operation where grid-connected parties can generate their own energy, usually through Renewable Energy Sources (RESs) and share it with each other locally[17]. P2P business models are still not very common due to the rigid energy market structures and regulatory frameworks[18] based on the B2C model we are all a acquainted with. Besides the technology-based advances, the business model transformation in the energy sector is driven also by the "collaborative economy" principle which is transforming energy customers into more proactive customers i.e., "prosumers" who have production and storage capabilities and can share the electric energy they produce[19].

[17] Review of Existing Peer-to-Peer Energy Trading Projects, Chenghua Zhang, Jianzhong Wu, Chao Long, Meng Cheng, May 2017

[18] A Novel Peer-to-Peer Energy Sharing Business Model for the Portuguese Energy Market, Lurian Pires Klein, Aleksandra Krivoglazova, Luisa Matos, Jorge Landeck and Manuel de Azevedo, December 2019

[19] Peer-to-peer and community-based markets: A comprehensive review, Tiago Sousaa, Tiago Soaresb, Pierre Pinsona, Fabio Moreta, Thomas Barochec, Etienne Sorina, April 2019

In the last decade, many new products and services governed by innovative business models have entered the energy market thanks to the use of big data and analytics[20]. Some examples are depicted in the table below.

Company name	Value proposition	Customers	Value delivery
Adaptricity www.adaptricity.com	A cloud-based grid analytics platform which allows distribution grid operators to better understand, operate and plan their electric grid infrastructure using data-driven grid analysis. This allows for significant cost savings in grid operation, grid maintenance, grid planning and asset management.	Distribution grid operators	Adaptricity offers four data-based software solutions: • Adaptricity.Plan for grid planning • Adaptricity.Sim for time-series based grid analysis and planning • Adaptricity.Mon for continuous distribution grid monitoring
EQuota Energy equotaenergy.com	An energy intelligent management service provider. Based on AI and Big Data, it provides energy efficiency optimization, operation and maintenance monitoring, carbon emission management, energy planning, electricity sales services, micro-grid services and other industrial chain technology solutions.	Commercial and residential customers	EQuota Energy offers EQuota Insight for smart energy management services based on AI algorithm model and data processing technology. A light version of the solution is also available called EQuota InsightLite.
Fresh Energy www.getfresh.energy	A customer-centric solution that analyses data collected from smart meters to enable utilities in providing enhanced services and high customer experience	Utilities	Fresh Energy offers a plug&play, customer centric, hardware agnostic solution. It analyses the data from customer's Smart Meters using complex algorithms, pattern recognition and machine learning, to identify how much power each consumer uses and how much that will cost them
BeeBryte	AI-driven optimization software for cooling &	Commercial and	BeeBryte offers a set of services which through AI minimise

[20] Digitalisation of New Business Models in the Energy Sector, University of Cambridge, June 2019

www.beebryte.com	refrigeration systems enhancing operational efficiency, reliability and comfort generating up to 40% savings.	residential customers	utility bills with automatic control of heating-cooling equipment, pumps etc. If solar generation is present, it is used for maximising self-demand.
Jungle AI www.jungle.ai	A platform for renewable energy generation based on AI and Machine Learning. It promises to reduce unplanned downtime, react quickly by detecting faults early on.	Renewable energy assets owners	Jungle AI offers two products/services: • Canopy to reduce downtime by detecting impending failures ahead of time and to increase power output by detecting underperformance issues • Power Forecasting to allow to reduce the cost of variability of the power output of large-scale wind- and solar farms.

Table 3 Big data analytics products new business models

5. Big Data impacts on the energy services

As stated in section 2, the processes throughout the energy value chain from generation to transmission and finally distribution are of key importance to ensure the energy usage and the availability of energy services for the prosumers.

The electric network is widely considered to be among the most critical infrastructure in the world, especially in advanced economies. In particular, the power sector is seen as uniquely critical for the "enabling function" it provides across all critical infrastructure sectors. Services like transport, finance and water supply are among the most highly dependent on the energy network and would be severely impacted in case of failure, leaving the population, in a word, vulnerable.

The electric grid, increasingly becoming more commonly known as smart grid, represents the backbone for many energy related services beyond the basic usage of the electricity, and so, ensuring the correct operation of all its assets, as well as protect them from external attacks has been one of the main concerns in the energy domain for the last years.

The benefits for the energy sector derived from the use of big data are diverse, implying huge economic impacts:

- Energy asset management
- Weather forecasting from historical data
- Reduce load intervention in the power grid
- Optimize smart grid operation and increase energy efficiency
- Ensure energy delivery and distribution to enable final services
- Improve service quality

- Analyse the utility industry
- Fault detection and advance warning
- Grid stabilization and management

There are several sources of data in smart grids, and important efforts and progress have been made for using the field data acquired from smart devices mounted in substations, feeders, etc… to enable the prediction of grid states, provide situational awareness, analyse grid stability, detect faults and provide advance warning. The major benefits of performing analytics include increased customer satisfaction, better resource utilization and improved quality of service. However, to conduct analytics, a proper data acquisition framework is required to collect, process, and analyse the data.

Analytics can be applied to signal, event, state, engineering operations, and customer analytics, in sum enabling high-level and detailed insights into grid situational awareness. There are several types of analytics models, namely descriptive, diagnostic, predictive, and prescriptive models. These can be applied for the smart grid, for instance, descriptive models describe customer behaviours for demand response programs. Diagnostic models are used to understand specific customer behaviours and analyse their power-related decisions. Each type of model can provide valuable input to create models that predict future customer decisions and hence, power needs. Finally, prescriptive models can provide high level analytics to influence smart grid marketing, engagement strategies and decision making. To further develop the main impacts related to the project, the implications of big data on the energy efficiency and unavailability are described in the following sections.

5.1 Energy efficiency

The impact of the Big data on energy services is very important because it allows us to generate digital twins which, thanks to the IoT and AI, allow us to develop and verify new energy efficiency measures before implementing them in the real pilot.

In addition, with the models generated, it allows us to make a change from a corrective and therefore traditional control system to a predictive system that adjusts not only to moments of lower production costs. It also allows us to overlap production curves with demand curves in the case of renewable energies.

It is a proven fact that ESCOs are investing more and more in techniques and technologies that allow us to centralise all the information and train models in different scenarios and even help us in the design phases of the installations.

As part of the PLATOON project, an exhaustive analysis of all the data from the pilots will be carried out to generate patterns that will allow us to carry out optimised energy management and optimise the demand of energy produced by renewable sources on site.

5.2 Unavailability

The feasibility of data to generate the models is fundamental in the previous and training phases and becomes less relevant as time goes by and with the models trained. Because thanks to the training carried out and provided that the results are comparable, the absence of data can be replaced with other data generated from the models.

The problem of the lack of data in the initial phases is very serious, when you still do not have models since all the conclusions, services or later developments can have a very high uncertainty falsifying the results.

We must consider that for systems based on big data to find correlations and be able to generate models or patterns, they must do so through statistical analysis, trends, artificial neural networks or decision trees and train with different time series to be able to generate reliable models. Therefore, all systems must have local backups that allow lost data to be recovered and allow the systems to work on an island.

5.3 Other impacts

The experience developed in other projects of the H2020 framework has shown us that it is feasible to achieve a reduction in energy demand of 20% through the application of techniques related to the Big data, since thanks to them it is possible to provide dynamism to the systems and to operate the installations in optimal operation points in a dynamic way according to the needs of the moment.
According to NIST[21], the benefits of modernization of power grids are as high as five times the one-time development cost[22]. Initial assessments by the American Council for an Energy-Efficient Economy predict the use of information and communication technology (ICT) and smart appliances would save about $80 billion in America's annual electricity bill[23].

6. PLATOON use cases and the expected impacts

While section 5 of the document focused on the impact of big data on the energy services and its implications on the energy efficiency and unavailability, this section focuses on measurable impacts of PLATOON use cases regarding each one of its seven pilots. The approach is to move from the use cases to measurables indicators of the impact.
An overview of PLATOON business KPIs is first provided, then, the low-level use cases (from D1.1 Business case definition, requirements and KPIs report- expected) expected impacts and related KPIs are presented.

6.1 PLATOON KPIs

The following table provides an overview of the KPIs that have been provided on the project technical agreement and listed from 1 to 6 as expressed impacts. The impacts numbers 5 and 6 are not categorized as business impacts but as consortium impacts. The impact "Increased in standards for data sharing, exchange and integration" is part of WP8.5 delivery and the impact "Emergence of sustainable ecosystems around digital platforms and strengthened links with other programs and initiatives, supported by regional, national and European policies and funds" is part of WP7 & WP9 deliveries.

[21] https://www.nist.gov
[22] National Institute of Standards and Technology, "Strategic R&D Opportunities for the Smart Grid: Advancing Measurement Science and Standards for Smart Grid Technologies," pp. 1-36, 2013, [Online] Available: http://www.nist.gov/smartgrid/upload/Final-Version-22-Mar-2013-Strategic-R-D- Opportunities-for-the-Smart-Grid.pdf.
[23] J.A. Laitner, M.T. McDonnell and K.E. Martinez, "The Energy Efficiency and Productivity Benefits of Smart Appliances and ICT Enabled Networks: An Initial Assessment," American Council for an Energy-Efficiency Economy (ACEEE), 2014. [Online] Available: http://aceee.org/research-report/f1402.

Expressed Impacts	Impacts sub level 1	KPI sub level 1	Impacts sub level 2	KPI sub level 2	Impacts sub level 3	KPI sub level 3	Impacts sub level 4	KPI sub level 4
1. Effective integration of relevant digital technologies in the energy sector, resulting in integrated value chains and efficient business processes of the participating organizations	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains	KPIs: 1)100% successful integration testing (deliverable D5.5). 2) Number of large-scale pilots where the reference architecture is implemented (target value: 7).	1.2 Efficient business processes	KPI: 10% improvement of existing business processes in terms of time, cost, process effectiveness, etc.				
2. Enhancing energy asset management, increasing consumer participation and innovative network management, creating new data-driven business models and opportunities and innovative energy services	2.1 Enhance asset management	KPIs: 1) Number of detected events - Target: predict equal or more failures compared to current techniques.	2.2 Increasing consumer participation	KPI: 10% increase of new contract schemes that reward flexible capacity.	2.3 Innovative network management	KPI: Accuracy increase compared to the current algorithms.	2.4 Creating new data-driven business models, opportunities, and innovative energy services	KPI: 10% revenue increase due to new data driven business models and services.
3. Contribution to increasing the use of renewable energy and increased energy efficiency based on optimised energy asset management, offering access to cheaper and sustainable energy for energy consumers and maximising social welfare	3.1 Increasing the use of renewable energy	KPI: 1) 10% increase in effective utilization of available RES. 2) Reaction time - Target: predict failures 50% earlier compared to current techniques. 3) False Positives - Target: generate less false positives than current techniques.	3.2 Increased energy efficiency	KPI: 15% energy savings compared to the current baseline.	3.3 Cheaper and sustainable energy for consumers and maximising social welfare	KPIs: 1) 20% savings in energy cost. 2) 20% saving in CO2 emissions.	3.4 Carbon reduction	

4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes		KPIs: 1) N. of available generic big data tools in the data analytics toolbox consumed in pilots - Target Value: 4. 2) N. of available energy specific tools in the data analytics toolbox consumed in pilots- Target Value: 10.						
5. Increased in standards for data sharing, exchange, and integration.		KPI: Number of contributions to existing standards- Target value: 8.						
6. Emergence of sustainable ecosystems around digital platforms and strengthened links with other programmes and initiatives, supported by regional, national, and European policies and funds.		KPIs: 1) Nº Additional supportive partners engaged - Target Value: 20 2) Nº Ambassadors engaged - Target Value: 6 3) Nº of collaboration with external exploitation partners: 20. 4) Number of collaborations with other regional, national and European programmes - Target Value: 50.						

Table 4: Expressed Impacts and associated KPIs[24]

In the next sub chapters, each sub-impact has been processed over all pilots based on the 4. KPI that are described are either technical or business. To keep a better understanding of the business value and on its score, we kept the technical and mark for some of them the direct or indirect relation with the business impact.

Please note:

- Table 4 is identified numbered objectives that will have to be rationalized and compared during the RUN phase on each pilot.
- Only the KPIs highlighted in green are considered as business KPIs.

[24] PLATOON GA

[24] D1.1 Challenges/ Business case definition

6.2 Pilot 1a: Predictive maintenance of wind farm

Key performance indicators						Business Impacts
Key performance indicators LLUC P-2a-01 Predictive maintenance of wind Farm						
ID	**Name**	**Business achievement**	**Description**	**Reference to mentioned use case objectives**	**expected impact**	**Description**
1	Modeling quality	Maintenance costs; Increase of RES usage; Detection	Modelling approach capable to fit healthy component data	O.1	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.4 Creating new data-driven business models, opportunities, and innovative energy services
2	Integration	Maintenance costs; Availability / Increase of RES usage	Tool interaction/integration	O.1, O.2	low	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes
3	Detection	Availability	Anomaly detection speed + accuracy (false vs true positives)	O.2	high	3.3 Cheaper and sustainable energy for consumers and maximizing social welfare
4	Load characterization	Increase of RES usage	Important historical loading events can be captured using automated methods	O.4	low	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation and test purposes
5	Processing reach	Maintenance costs Availability / Increase of RES usage	Size of fleet dataset that can be analyzed automatically: number of turbines, channels,…	O.1, O.2	middle	1.2 Efficient business processes
6	Processing speed	Maintenance costs	Speed of the anomaly analysis	O.2	middle	1.2 Efficient business processes 1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains
7	Maintenance costs		Maintenance cost reduction	O3, 04	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business

						processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities and innovative energy services
8	Availability / Increase of RES usage		Increase availability of Wind Turbines (increase RES usage)	O3, 04	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.4 Creating new data-driven business models, opportunities and innovative energy services 3.0 Contribution to increasing the use of renewable energy and increased energy efficiency based on optimized energy asset management, offering access to cheaper and sustainable energy for energy consumers and maximizing social welfare 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes 3.4 Carbon reduction

Table 5 Pilot 1a: Predictive maintenance of wind farm KPIs and expected impacts

6.3 Pilot 2a: Electricity balance and predictive maintenance

Key performance indicators						Business Impacts
Key performance indicators LLUC P-2a-01- LLUC P-2a-07						
ID	**Name**	**Business achievement**	**Description**	**Reference to mentioned use case objectives**	**expected impact**	**Description**
KPI-1	Improved forecasting accuracy		Deployment of new forecasting models (artificial intelligence methods and neural networks, hybrid models)	LLUC P-2a-03 LLUC P-2a-04		1.2 Efficient business processes
KPI-2	Savings from tertiary		Increase the annual net savings from tertiary	LLUC P-2a-01	high	2.3 Innovative network management

	reserve trading		reserve trading, see CIGRE 2020[i]			
KPI-3	Better demand response		Responding better to changes in demand	LLUC P-2a-01 LLUC P-2a-02 LLUC P-2a-03	high	2.4 Creating new data-driven business models, opportunities, and innovative energy services 1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes
KPI-4	Improved RES integration		Better evaluation of the effects from RES integration	LLUC P-2a-02 LLUC P-2a-05	middle	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 3.1 Increasing the use of renewable energy 3.4 Carbon reduction
KPI-5	Balanced energy mix		Reduction in peak use of fossil fuels	LLUC P-2a-02 LLUC P-2a-04	middle	3.2 Increased energy efficiency 3.1 Increasing the use of renewable energy 3.4 Carbon reduction
KPI-6	Curtailment avoidance		Percentage of curtailment avoidance	LLUC P-2a-04 LLUC P-2a-05	middle	3.2 Increased energy efficiency 1.2 Efficient business processes
KPI-7	Portfolio optimization		Improved portfolio optimization of Balance Responsible Parties (Optimization/Management of Renewable Energy Systems)	LLUC P-2a-04	high	3.2 Increased energy efficiency
KPI-8	Saving costs		The installation of the machine learning algorithm for detection of abnormal behavior shall reduce the maintenance costs.	LLUC P-2a-07	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities and

						innovative energy services
KPI-9	Increased stability		Increased degree of stability in the real power plant operation.	LLUC P-2a-05 LLUC P-2a-07	high	1.2 Efficient business processes
KPI-10	Metadata models		Number of metadata specifications prepared and registered with CKAN related to the data that will be used in the analytical services	LLUC P-2a-06		

Table 6 Pilot 2a: Electricity balance and predictive maintenance KPIs and expected impacts

6.4 Pilot 2b Electricity grid stability, connectivity, and life cycle

Key performance Indicator					**Business Impacts**	
ID	**Name**	**Business achievement**	**Description**	**Reference to mentioned use case objectives**	**expected impact**	**Description**
Key performance Indicators LLUC P-2b- 01 - Predictive Maintenance for MV/LV Transformers-virtual sensor						
1	Temperature estimation accuracy (%)	Savings (€) Additional Costs (€) Anticipation time (days)	Hourly temperature accuracy estimation based on estimated temperature (ET) and actual (measured) temperature (AT) for top oil: (ET-AT)/AT (%)			
Key performance indicators LLUC P-2b- 01 - Predictive Maintenance for MV/LV Transformers						
1 2	True positives (TP)	Savings (€) Additional Costs (€) Anticipation time (days)	Number of anomalies detected with early warnings and confirmed with a corrective work order			
3	False positives (FP)	Savings (€) Additional Costs (€) Anticipation time (days)	Early warnings with no associated corrective work order			

4	False negatives (FN)	Savings (€) Additional Costs (€) Anticipation time (days)	Corrective work order without a previous early warning			
5	True Negatives (TN)	Savings (€) Additional Costs (€) Anticipation time (days)	No early warning and no work order			
6	Specificity (%)	Savings (€) Additional Costs (€) Anticipation time (days)	Proportion of true negatives relative to all negative cases (TN/(TN+FP))			
7	Sensitivity (%)	Savings (€) Additional Costs (€) Anticipation time (days)	Proportion of actual positives correctly identified (TP/(TP+FN))			
8	Cohen's Kappa (%)	Savings (€) Additional Costs (€) Anticipation time (days)	Measurement of matches in the predictive tool discounting the probability of randomly matching			
9	Savings (€)		Cumulative measurement of savings associated to True Positives considering a) Avoided breakdown consequences + b) Downtime cost		middle	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities, and innovative energy services
10	Additional Costs (€)		Increased costs due to maintenance activities associated to False Positives. They should be subtracted from Savings to get the net value.		high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities, and innovative energy services
11	Anticipation time (days)		For each True Positive it represents the delta Time between the moment of detection and the time of failure		high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.4 Creating new data-driven business models, opportunities, and innovative energy services 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes

Key performance indicators LLUC P-2b- 01 - Predictive Maintenance for MV/LV Transformers -Asset Health

1 **2**	Risk decrease (€)		Risk decrease comparing risk-based maintenance supported by the tool to the ordinary preventive maintenance (equal maintenance expenditure is assumed in both cases)		high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities and innovative energy services
3	Maintenance cost savings (€)		Maintenance cost savings comparing risk-based maintenance supported by the tool to the ordinary preventive maintenance (equal risk level is assumed in both cases)		high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities, and innovative energy services
4	Useful Life Extension (years)		Based on the estimation of the RUL (Remaining Useful Time) it indicates the achievable extension of life relative to that indicated by the manufacturer		high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.4 Creating new data-driven business models, opportunities, and innovative energy services 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes
Key performance Indicators LLUC P-2b- 02- Non-technical loss detection in Smart Grids						
NTL-KPI-01 **NTL-KPI-02**	Global Losses Energy Percentage		Percentage of the energy that is provided from a MV substation or LV CT that is not settle to any consumer and is therefore lost. To be averaged in long periods (at least months). NTL-KPI-01 = NTL-KPI-02 + NTL-KPI-03	Quantification of losses in the distribution grid of a DSO		
NTL-KPI-02 **NTL-KPI-03**	NTL Energy Percentage		Percentage of the energy that is provided from a MV substation or LV CT that is lost due to NTL	Detection of non-technical losses		

			NTL-KPI-02 = NTL-KPI-04 + NTL-KPI-05			
NTL-KPI-04	NTL Energy Percentage		Percentage of the energy that is provided from a MV substation or LV CT that is lost due to NTL	Detection of non-technical losses		
NTL-KPI-05	Customer NTL Energy Percentage		Percentage of the energy that is provided from a MV substation or LV CT that is lost due to fraud executed by customers. This portion of NTL is more likely to be avoided after it is detected, as legal actions can be taken against the connection point contractors.	Detection of non-technical losses		
NTL-KPI-06	Customer NTL Energy Percentage		Percentage of the energy that is provided from a MV substation or LV CT that is lost due to fraud executed by non-customers. This energy is stolen by non-permitted connections to the grid, which are difficult to be located physically.	Detection of non-technical losses		
NTL-KPI-06 **NTL-KPI-07**	True positives (TP)		Number of customers identified as fraud authors in the NTL identification scenario which are verified to be committing fraud	Detection of non-technical losses		
NTL-KPI-08	False positives (FP)		Number of customers identified as fraud authors in the NTL identification scenario which are not committing fraud, as result of a verification action	Detection of non-technical losses		

NTL-KPI-08 NTL-KPI-09	False negatives (FN)		Number of customers which are not identified as fraud authors in the NTL identification scenario but are really committing fraud	Detection of non-technical losses		
NTL-KPI-10	True negatives (TN)		Number of customers which are not identified as fraud authors in the NTL identification scenario, and are not really committing fraud	Detection of non-technical losses		
NTL-KPI-11	Specificity (%)		Proportion of true negatives relative to all negative cases (TN/(TN+FP))	Detection of non-technical losses		
NTL-KPI-12	Sensitivity (%)		Proportion of actual positives correctly identified (TP/(TP+FN))	Detection of non-technical losses		
NTL-KPI-13	Cohen's Kappa (%)		Measurement of matches in the NTL identification scenario discounting the probability of randomly matching	Detection of non-technical losses		

Table 7 Pilot 2b Electricity grid stability, connectivity, and life cycle KPIs and expected Impacts

6.5 Pilot 3a Office building: operation performance thanks to physical models and IA algorithms

Key performance Indicators					**Business Impacts**	
ID	**Name**	**Business achievement**	**Description**	**Reference to mentioned use case objectives**	**expected impact**	**Description**
Key performance Indicators LLUC P-3a-01- Optimizing HVAC control regarding occupancy						
KPI-1	Comfort during occupancy time		Comfort evaluated thanks to air temperature in the building in function of occupancy time. Percentage of occupancy below a certain level of comfort will be evaluated.	Optimizing comfort	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities and innovative energy services 3.3 Cheaper and sustainable energy for consumers and maximising social welfare

KPI-2	Unnecessary HVAC heating or cooling indicator		Evaluate the percentage of energy emission that was unnecessary regarding the actual building occupancy. It is based on the controls of heating or cooling (percentage of valve) during unoccupied period	Optimizing energy demand and GHG emissions		
KPI-3	Gas and electricity Consumption by occupancy hour		Amount of gas and electricity demand used for heating and cooling by occupancy hour of the building for a given period (a month, a year)	Optimizing energy demand and GHG emissions	low	3.2 Increased energy efficiency
KPI-4	Climate adjusted Gas and electricity Consumption by occupancy hour		Amount of gas and electricity demand used for heating and cooling, normalized for a given climate, by occupancy hour of the building for a given period (a month, a year)	Optimizing energy demand and GHG emissions		
Key performance Indicators LLUC P-3a- 02 - Providing Demand Response Service through HVAC control						
KPI-1	Availability of demand response services provided over a certain period (month, year)		Percentage of days (%) where demand response services can be provided for a given offset capacity, in terms of power (kW) and/or energy (kWh). Specific time slots during the day can be targeted	Contribute to the grid management (reduce peak demand offset)	high	2.4 Creating new data-driven business models, opportunities, and innovative energy services 1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes
KPI-2	Load offset capacity offered over a certain period (month, year)		Offset capacity, in terms of power (kW) or energy (kWh), available for a given percentage of days where the service is available. Specific time slots during the day can be targeted	Contribute to the grid management (reduce peak demand offset)	high	2.4 Creating new data-driven business models, opportunities, and innovative energy services 1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation and test purposes

KPI-3	Error on the HVAC load prediction over a certain period (no demand response event)		Error (%) on the HVAC load prediction calculated every 30min as the errors between the predicted and the realized energy demand, divided by the predicted one (when HVAC is operating). The error can be characterized over the period: mean, standard deviations, daily distribution, seasonal distribution.	Provide accurate prediction to the aggregator		
KPI-4	Error on the flexibility prediction		Error (%) on the "use" of the building thermal inertia in comparison with the prediction in case of the implementation of a flexibility event. It is related to the temperature drop in the building in comparison with the prediction.	Provide accurate prediction for the aggregator		
KPI-5	Error on the HVAC load prediction for days with load shifting programs		Error (%) on the HVAC load prediction calculated every 30min as the errors between the predicted and the realized energy demand, divided by the predicted one (when HVAC is operating). The error can be characterized over the period: mean, standard deviations, distribution during Demand response event.	Provide accurate prediction to the aggregator		
KPI-6	Capacity to answer load interruptions request or programs from the Aggregator		Statistics concerning the implementation of the demand response request from the aggregator. The capacity to answer partially or totally the requests will be analysed.	Respect the contract with the aggregator (and generate income)	high	2.4 Creating new data-driven business models, opportunities, and innovative energy services 1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes

Table 8 Pilot 3a Office building: operation performance thanks to physical models and IA algorithms KPIs and expected impacts

6.6 Pilot 3b Advanced energy management system and spatial (multi-scale) predictive models in the smart city

Key performance indicators					Business Impacts	
ID	**Name**	**Business achievement**	**Description**	**Reference to mentioned use case objectives**	**expected impact**	**Description**
Key performance indicators LLUC P-3b-01 Building Heating & Cooling demand Analysis and Forecast						
PI_01_KPI01	PUE Decrease	CO2 Cost saving	% of reduction of PUE (by comparison with similar building or historical data) $PUE = \frac{(PUE_{old} - PUE_{new})}{PUE_{old}} \times 100$	- Energy efficiency plans (heating, cooling) - Daily and hour energy demand forecast - Building energy usage benchmark - Ensure energy saving and costs reduction on selected buildings	Low	
PI_01_KPI02	kWh/Y/sqm	CO2 Cost saving	% of energy demand reduction (before/after) for each type of building	- Energy efficiency plans (heating, cooling) - Daily and hour energy demand forecast - Building energy usage benchmark - Ensure energy saving and costs reduction on selected buildings	high	
PI_01_KPI03	kWh/Y/sqm	CO2 Cost saving	% of energy demand reduction (heating, cooling) for line of use of each type of building	- Daily and hour energy demand forecast - Building energy usage benchmark - Ensure energy saving and costs reduction on selected buildings	high	
PI_01_KPI04	CO2	CO2	% of CO2 emission reduction	- Reduction of emissions (CO2 / TOE correlation)	high	3.3 Cheaper and sustainable energy for consumers and maximising social welfare 3.4 Carbon reduction
PI_01_KPI05	Costs €	Energy usage reduction Economic benefit at standard price	Euros (€) saved			1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities, and innovative energy services
Key performance indicators LLUC P-3b-02 Predictive maintenance of cooling & heating systems						

PI_02 _ K01	Mean Time Between Failure (MTBF) increase	Availability	MTBF increase in heating and cooling plants due to the predictive analysis (expressed in %)	- Improve plants efficiency -Technical plants fine tuning - Increase the availability of heating/cooling plants	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.4 Creating new data-driven business models, opportunities, and innovative energy services 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes
PI_02 _ K02	Maintenance cost reduction (cost/y/sqm)	Reduce maintenance costs (number of emergency tickets) Reduce maintenance costs (emergency tickets in %)	Evaluation of maintenance cost reduction for each building or total referred to the heating and cooling plants (expressed in %)	- Improve plants efficiency - Reduce maintenance costs	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities, and innovative energy services
Key performance indicators LLUC P-3b-03 Lighting Consumption Estimation & Benchmarking						
PI_03 _ K01	Energy demand/ people presence	Reduce energy demand for lighting	Value of demand of the light plants compared with the number of people in the building	- Identify the correlation between the number of building user and the lighting demand	Low	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities, and innovative energy services
PI_03 _ K02	Lighting Cost saving	Reduce energy demand for lighting (% of building energy demand or KWh for lighting / sqm)	% of cost saving due to the adoption of new lighting lamps for each type of building	- Estimation and benchmarking between different lighting solutions - Optimization and reduction of lighting demand	Middle	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities, and innovative energy services
PI_03 _ Knew	Lighting demand deviation	Increase lighting demand forecast accuracy	Deviation between actual and estimated lighting demand (expresses in %)		Middle	

PI_03 _ K04	Lighting demand reduction	Reduce energy demand for lighting	% of demand reduction due to the adoption of new lighting lamps for each type of building	- Estimation and benchmarking between different lighting solutions - Optimization and reduction of lighting demand	Middle	
PI_03 _ K04	GHG emissions	CO_2 reduction	% GHG emissions per square meter due to lighting in different scenarios	- Estimation and benchmarking between different lighting solutions - GHG emission reduction	Middle	3.3 Cheaper and sustainable energy for consumers and maximising social welfare 3.4 Carbon reduction

Table 9 Pilot 3b Advanced energy management system and spatial (multi-scale) predictive models in the smart city KPIs and expected impacts

6.7 Pilot 3c Energy efficiency and predictive maintenance in the smart tertiary building hubgrade

Key performance Indicator					**Business Impacts**	
ID	**Name**	**Business achievement**	**Description**	**Reference to mentioned use case objectives**	**expected impact**	**Description**
Key performance Indicator LLUC P-3c 01 Advanced EMS for Tertiary Buildings						
KPI-01	Energy Bill reduction		The KPI will evaluate the energy bill reduction achieved	Reduce the energy bill	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities, and innovative energy services
KPI-02	RES ratio		The KPI will evaluate the RES usage versus overall energy consumption.	Maximize the RES usage	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.4 Creating new data-driven business models, opportunities, and innovative energy services 3.0 Contribution to increasing the use of renewable energy and increased energy efficiency based on optimised energy asset management, offering access to cheaper and sustainable energy for energy consumers and maximising social welfare 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes 3.4 Carbon reduction
Key performance Indicator LLUC P-3c 02 Predictive Maintenance in Smart Tertiary Building Assets						

AV-01	Availability		It is the availability of the asset in a period. As a mathematical formula it would be equal to Working Time divided by Total Time. We can consider Total Time as the time that the asset must be working or the physical time (24 hours a day)	The objective is to increase the availability of the assets	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.4 Creating new data-driven business models, opportunities, and innovative energy services 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes
UL-01	Useful Life		It is important to maximize the useful life of each asset. This is done based on various concepts: · Early detection of possible breakdowns · Correct performance of own maintenance tasks (corrective / preventive) · Working with assets in suitable conditions for them (not forcing work in unsuitable conditions, etc.) The mathematical formula is the total time (in hours) that the asset has operated until it has finally been replaced	The objective is to increase the useful life of the assets	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.4 Creating new data-driven business models, opportunities, and innovative energy services 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes
MC-01	Maintenance Costs (Total maintenance costs)		The maintenance cost of an asset is the sum of the costs of the work orders that have been carried out on that asset. It is important to indicate that maintenance costs may be higher in some assets that use predictive maintenance. Therefore, the goal should be achieving the lowest possible cost in the set of assets. Thus, the formula is the sum of the maintenance costs of the assets selected for the use case.	The objective is to reduce the total maintenance costs of the assets	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities, and innovative energy services

Table 10 Pilot 3c Energy efficiency and predictive maintenance in the smart tertiary building hubgrade KPIs and expected impacts

6.8 Pilot 4a Energy management of microgrids

Key performance indicators					Business Impacts	
Key performance indicator LLUC P-4a- 01 - Energy Management of Microgrids						
ID	**Name**	**Business achievement**	**Description**	**Reference to mentioned use case objectives**	**expected impact**	**Description**
kpi-1	Energy availability		Optimal energy demand (increase in energy availability)	Optimization for renewable electricity generation Smart storage/generation	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.4 Creating new data-driven business models, opportunities, and innovative energy services 3.0 Contribution to increasing the use of renewable energy and increased energy efficiency based on optimised energy asset management, offering access to cheaper and sustainable energy for energy consumers and maximising social welfare 4. Improving availability of big data and big data management & analysis facilities for real life scale research, simulation, and test purposes 3.4 Carbon reduction
kpi-2	Cost		Reduction of maintenance effort and costs	Optimization for renewable electricity generation	high	1.1 Effective integration of relevant digital technologies in the energy sector resulting in integrated value chains 1.2 Efficient business processes 2.1 Enhance asset management 2.4 Creating new data-driven business models, opportunities, and innovative energy services
kpi-3	Forecast	Energy availability Cost	Reduced forecasting errors	Generation and load forecast		
kpi-4	Realtime	Energy availability Cost	Ability to monitoring/analyse/optimize data and the system at real time rate	EMS with real-time processing Smart storage/generation		

Table 11 Pilot 4a Energy management of microgrids KPIs and expected impacts

7. Conclusion

This deliverable evaluates PLATOON project impacts with a focus on the opportunities to use big data use big data, advanced analytics, and open data to solve problems faced by the energy sector. It is strongly related to the WP6 - Large Scale Pilot Implementation and Validation, which however builds up upon the remaining work packages.

Energy sector from infrastructure perspective as well as from source efficiency, global competitiveness, and quality of life are very important for Europe. This deliverable provides first an overview of the available data sources, key challenges to unlock new innovative opportunities, their uses cases in the different categories of Big Data value, as well as energy efficiency, availability, customer experience and new business model helped identifying PLATOON stakeholders needs for big data applications. The evaluation of these needs and challenges demonstrated that the existing big data analytics technologies as employed by the business and big data platforms providers will not fully cater the energy sector and will not be sufficient. Therefore, the objectives defined within PLATOON and its seven large scale demonstrators will provide services and functionalities to take the big data analytics services and application in the energy sector beyond the state of the art. The PLATOON consortium will concentrate efforts to generate value by adapting and applying big data analytics technologies within their specific application domains all over the energy value chain and adding value-use cases. The outcomes of PLATOON will be applied for:

- Ensuring smart grid stability, load forecast (Pilot 2a-LLUC-03) and prediction of energy demand for planning and managing energy network resources and trading (Pilot 2a-LLUC-01 Pilot 2a-LLUC-02, Pilot 3a, Pilot 3b, Pilot 3c and Pilot 4a).
- Improving malfunction diagnosis and predictive maintenance, either on the production side (in plant facilities, see Pilot 1a, Pilot 2a-07, Pilot 2b, Pilot 3b and Pilot 3c) or health state estimation, and identifying locations and forecasting future line outages to decrease the outage costs and improve system reliability.
- Profiling user behaviours to adjust individual consumption patterns and to design policies for specific users (Pilot 2b, 3a, 3b and 3c).
- Advanced visualization is one of the key application area of big data analytics that can improve the overall assessment of smart grids. Big data analytics with the visualization technologies is used for monitoring real-time power system status as well as accurate grid connectivity information (All pilots).

Furthermore, to move from general impacts of PLATOON the cases to measurables indicators of the impact, the deliverable D8.1 provides an overview of the key indicators provided on the project agreement as expressed impacts. This KPIs will be evaluated within the different PLATOON uses cases, along the project using different assessment tools (Tests, simulations, or any other assessment tool).

It is important to note, that the KPIs metrics that drive the uses cases impacts shall be evaluated and challenged during the project. If needed, further updates can be added in the upcoming PLATOON deliverables.