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Digital platform and analytic tools for energy

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Abstract:	This report summarises the preliminary validation results of the different components developed in WP2, WP3 and WP4 for all the pilots and corresponding use cases. The validation is performed based on the KPIs identified in the validation plan as per explained in deliverable D6.6. This deliverable is the second version of deliverable D6.5 which was submitted in M30 and includes the updated and missing results evaluated after the V1 validation.
Keyword List:	Validation, KPIs, Impact assessment, Large Scale Pilots, Use cases.

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		Modification Reason	Modified by
V.01	31/03/2022	TOC	Erik Maqueda
V1.0	02/06/2022	Executive summary, introduction and general information for pilots. Added validation results from TECN for Pilot 1A, 2B and 3C	Erik Maqueda
V1.1	20/06/2022	Added missing information from rest of the pilots.	VUB, IMP, CS, SAM, IND, ENGIE, PI, ENG, ROM, SIS, PDM and IAIS.
V1.2	30/06/2022	Amendments after internal review	Erik Maqueda
V2.0	25/11/2022	Updates for pilot 3B-PI	Valeria Di Pasquale
V2.1	30/11/2022	Updates for pilot 1A and 2B and 3C	Xavier Chesterman, Adrià Serra, Eduardo Jimenez , Mikel Fernandez, Diana Manjarres, Ainhoa Pujana, Asier Gonzalez and Jorge Menoyo
V2.2	02/12/2022	Updates for pilot 1A and 2B	Xavier Chesterman, Adrià Serra, Eduardo Jimenez and Mikel Fernandez
V2.3	15/12/2022	Updates for missing pilots and common components	Valentina Janev, Lilia Bouchendoka, Patrick Maurelli, Adelaida Lejarazu, Borja Tellado, Marco Musetta and Tanseem Tazeen Rashid

Executive Summary

This report summarises the evidence and analysis of the preliminary validation results of the different components developed in WP2, WP3 and WP4 collected upon the execution of the large-scale pilots for all sites and use cases. The validation is performed based on the KPIs identified in the validation plan comparing them to the defined targets as per explained in deliverable D6.6. The validation report collates the conclusions from all stakeholders involved in the different pilots. Also, it contains the validation results of the PLATOON Common components which are cross-pilot. Finally, in the conclusions section an overall evaluation is done including the identification of the main pending aspects and risks.

This deliverable is the second version of deliverable D6.5 which was submitted in M30 and includes the updated and missing results evaluated after the V1 validation.

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List of Terms and Abbreviations

CA	Consortium Agreement
CO	Confidential
DM	Dissemination Manager
EC	European Commission
ES	Energy System
EM	Exploitation Manager
GA	Grant Agreement
GAM	General Assembly Meeting
IDS	International Data Spaces
MSLE	Mean Squared Logarithmic Error
PM	Project Manager
PML	Process Mastery Level
POD	Point of Delivery
PDR	Point of Re-delivery
PU	Public
QA	Quality Assurance
RE	Restricted
ReLU	Rectified Linear activation fUnction
SC	Steering Committee
TM	Technical Manager
WP	Work package
WPL	Work package Leader

1. Introduction

This report summarises the evidence and analysis of the preliminary validation results of the different components developed in WP2, WP3 and WP4 collected upon the execution of all large scale pilot sites and corresponding use cases. The validation is performed based on the KPIs identified in the validation plan defined in deliverable D6.6. This deliverable is structured in the following sections:
Sections 2-9 summarise the validation results and conclusions for all the large scale pilot sites and corresponding use cases.
Furthermore, section 10 contains the validation results of the PLATOON Common components which are cross-pilot.
Finally, there is a conclusions section where an overall evaluation is done.
Besides, Annex I explains the KPIs for the different pilots and common components which were initially defined for deliverable D6.6 and some of which have been updated.

2. Pilot 1A Evaluation & Validation Report

2.1 Introduction

This pilot focusses on wind farms both onshore and offshore with a specific focus on wind turbines in the range of 1.5-3MW owned by ENGIE in different locations across Europe. There is a single use case focused on predictive maintenance of wind turbine electrical drivetrain components which aims to:

1. Develop, implement and validate accurate physical and data-driven models of the wind turbine electrical drivetrain components: generator and power converter.
2. Develop anomaly detection methods for identification of unhealthy behaviour of the components in scope.
3. Develop an approach to convert the identified anomalies towards health indicators to create a diagnostic tool.
4. Extract the relevant events that the electrical drivetrain components are exposed to and have a potential negative effect on the lifetime of the electrical components.

2.2 LLUC-1A-01-Predictive maintenance of wind turbine electrical drivetrain components

This use case focuses on data analytics tools to accurately detect failures in the electrical components of wind turbines, limited specifically to the generator (doubly fed induction generator) and the power converter. In this use case two different approaches are used:

1. Hybrid-digital twin approach developed by TECN
2. Data driven approach developed by VUB

2.2.1 Evaluation and Validation

2.2.1.1 Hybrid-digital twin approach

Table 1: LLUC-1A-01-KPIs evaluation- Hybrid-digital twin approach

KPI #	Description	Target Value	Actual Value	Comments

1	Modelling quality	3%	Active Power – MAPE=2.33% Current – MAPE=2.66% Stator Winding Temperature – MAPE=4.33%	The error (for the active power and current parameters) is below the threshold value of 3%. However, the error for the stator winding temperature is above the target threshold.
2	Integration	1	1.0	All PLATOON components have been implemented and validated.
3	Fault Detection	Compared to the current failure detection the speed should improve with at least 25%, while keeping false positives below 10%	The new algorithms have not improved the current detection speed. However, the false positives have stayed the same.	Although the fault detection target value has not been achieved, the developed algorithm has proven to help the troubleshooting of the failed components. Besides, for V2 of this document we are currently working on new algorithms that include more features to try to improve the fault detection KPI.
4	Processing Capability	Full processing chain for a farm should be able to run on a standard server.	Full processing chain is able to run on a standard server.	The training part and dockerisation of the Digital Twin in Matlab showed a high consumption of RAM and CPU. However, once it is dockerised the execution phase is significantly less computationally expensive and can be run in any standard server with 4CPUs and 16GB RAM.
5	Maintenance costs reduction	1 M€	5 M€	On target. The business preferred to provide numbers in absolute values.
6	Availability increase	2-5%	0.01%	No availability increase as the downtime (3 weeks) for a generator replacement is low compared to total availability over the lifetime of the turbine.

To validate the data analytic tools for predictive maintenance of wind turbines developed in WP4, the tools have been trained and tested with data from several onshore wind farms from ENGIE all with data from Senvion units of 2MW.
Any data regarding turbine, identifier, location and date have been removed due to confidentiality issues.

Regarding the modelling quality KPI, for the Normality Digital Twin of the Electric Generator it can be noted that the results have significantly improved compared to the ones obtained for the 1.5MW GE units used for model development in WP4. This is due to the fact that the 2MW Senvion turbines have a torque sensor and, thus, we can use the measured torque directly as an input to the electromechanical digital twin. This reduces significantly the uncertainty linked to the aero-mechanical model due to different parameters (direction, density…) that affect on the effective wind speed. Figure 1 shows the comparison of real data (orange), simulated data using torque as input (blue) and simulated data using wind speed as input (yellow).

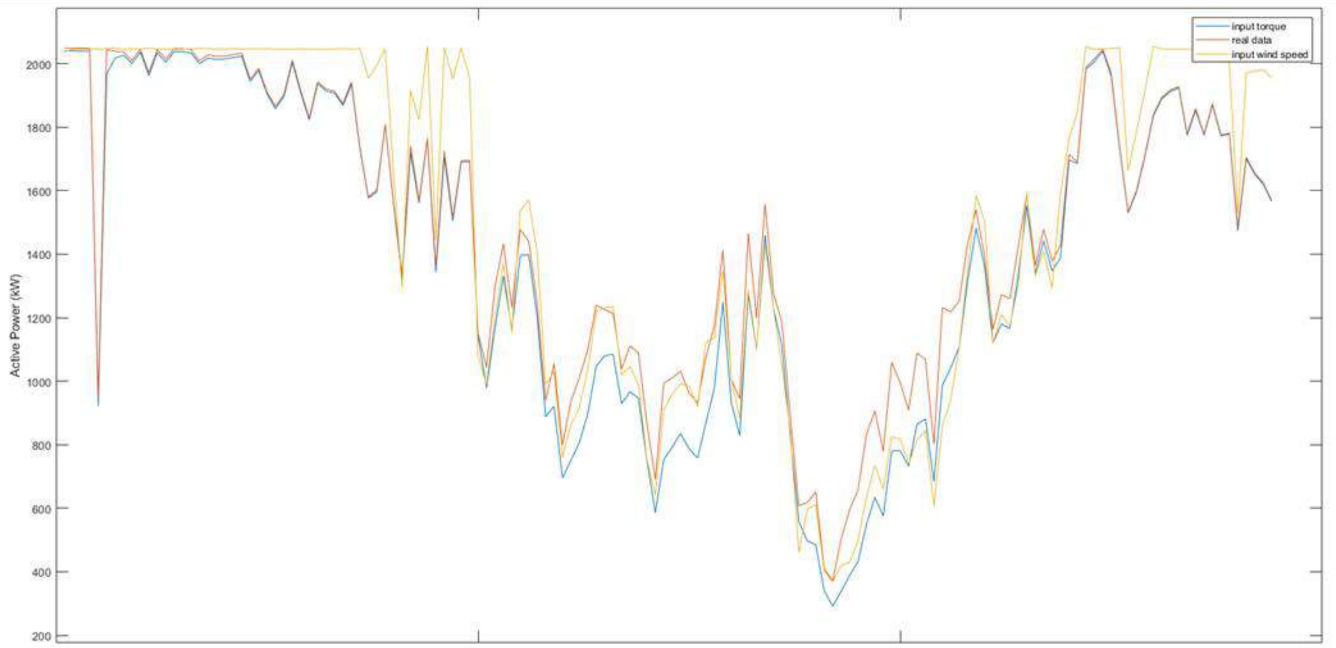


Figure 1: LLUC-1A-01-Normality Hybrid Digital Twin - Validation Results- Modelling quality - Active Power

¡Error! No se encuentra el origen de la referencia. Figure 2, Figure 3 and Figure 4 **¡Error! No se encuentra el origen de la referencia.**show the simulated (blue) and real data (orange) for active power, current and stator winding temperature parameters, respectively. As it can be noted the error for the stator winding temperature parameter is larger compared to the active power and current. In fact, the error for the active power and current parameters is below the threshold value of 3%, whereas, the error for the stator winding temperature is above the target threshold.

ACTIVE POWER

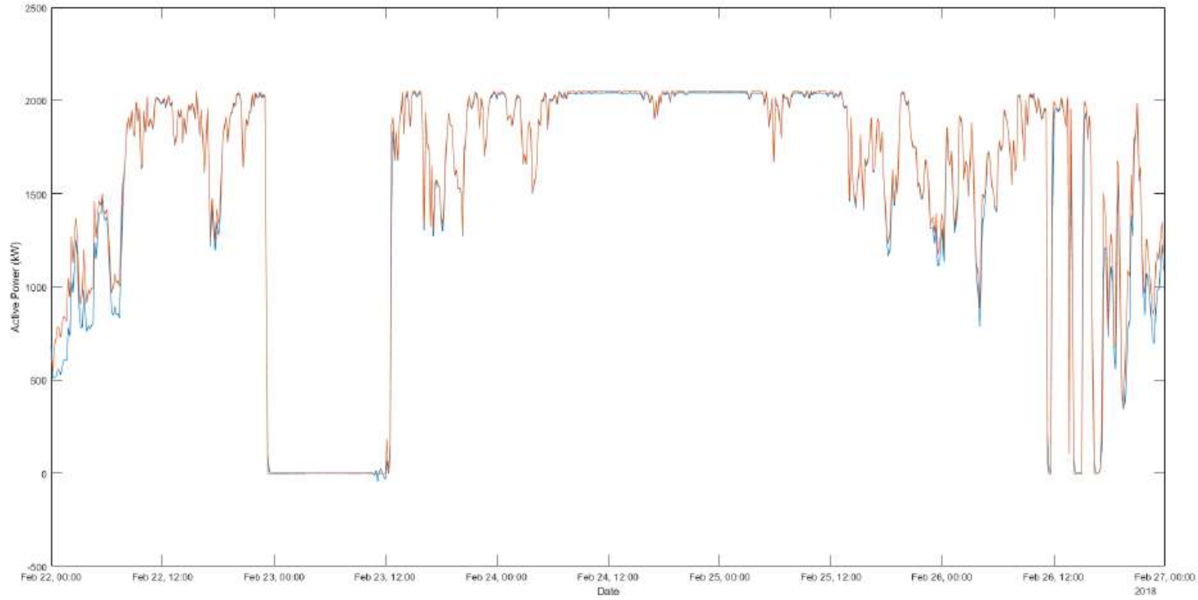


Figure 2: LLUC-1A-01-Normality Hybrid Digital Twin - Validation Results- Modelling quality- Active Power

CURRENT

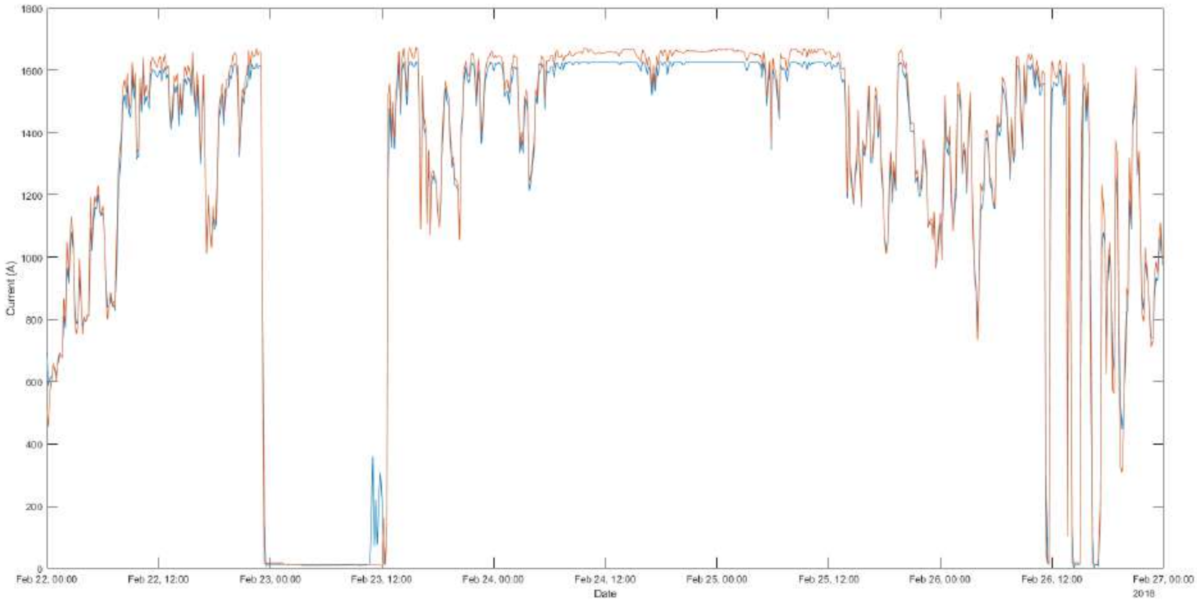


Figure 3: LLUC-1A-01-Normality Hybrid Digital Twin - Validation Results- Modelling quality- Current

STATOR WINDING TEMPERATURE

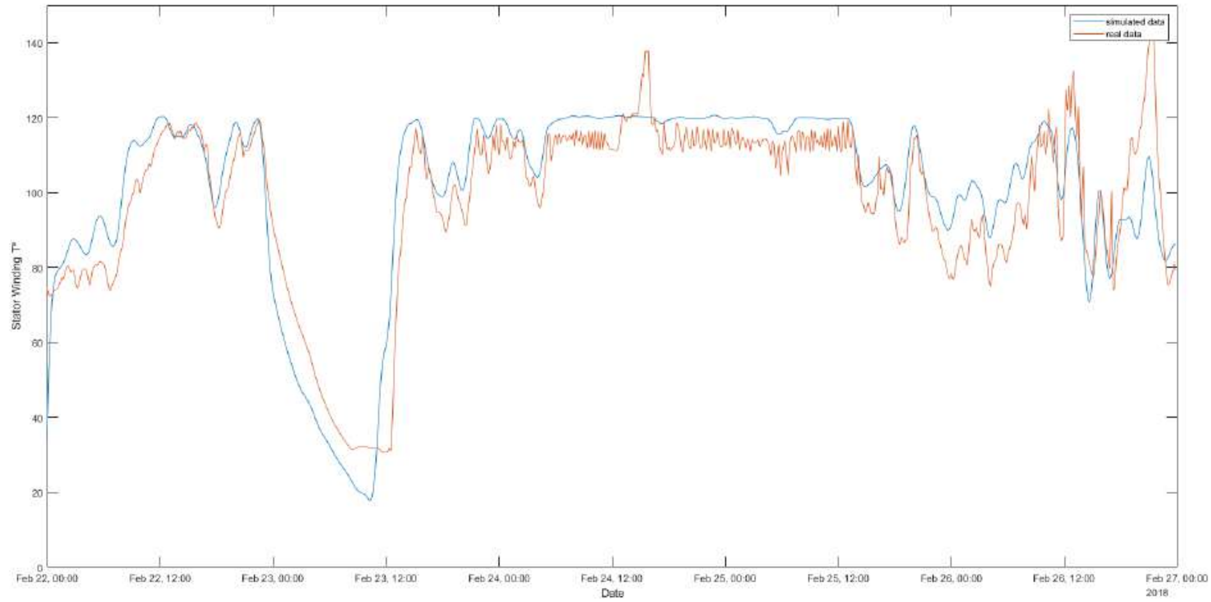


Figure 4: LLUC-1A-01-Normality Hybrid Digital Twin - Validation Results- Modelling quality- Stator Winding Temperature

Regarding the integration KPI, all the components have been successfully integrated and validated. The evidence for the implementation can be found in deliverable D6.7.

Regarding the fault detection KPI, the initial classifier developed in WP4 was validated and the results showed that it was only detecting anomalies but not failures. In fact, the selected parameters were selected to identify an over temperature. However, an overtemperature is not necessarily a symptom of a failure and could happen due to high ambient temperature conditions along with high wind speeds. The actual failure that ENGIE is interested in detecting is a "Generator Fan Failure". To be able to detect the failure the classifier has been improved using as the condition indicator the difference between the real and simulated stator winding temperature. The modified classifier was capable of detecting an issue over one month prior to the failure. These tests have been carried out for one of the wind turbines.

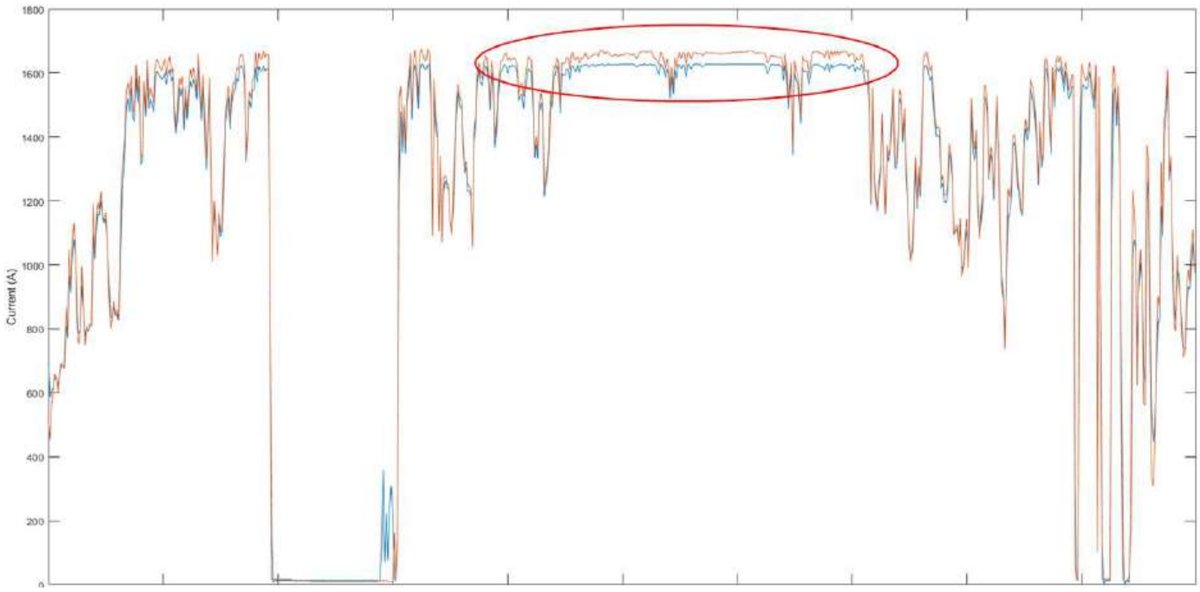


Figure 5: LLUC-1A-01-Failure Detection Classifier - Validation Results

However, from the failure identification date until the date when the fan was replaced the tool did not trigger anymore. This issue was validated with the operator who confirmed that there was a stator winding temperature sensor failure and the sensor was replaced. However, there were no further maintenance actions until the fan replacement. In addition, the developed data analytics tool was further validated with other labelled failures on other similar wind turbines and a similar pattern was observed. As a conclusion it was thought that the cause of the fan replacement could be due to a different reason of overtemperature (e.g. noise, vibration, etc.).

Therefore, from M30-M36 a new classifier was developed using new features and machine learning techniques as explained in deliverable D4.8. Samples from SCADA data and from simulated digital twin were labelled with actual failure modes using operation and maintenance orders report when failure mode events occur. The maintenance information provided is presented in the table below.

Table 2. information of maintenance reports

Wind turbine identification	Failure mode	Event date	Initial time window	Final time window
80284	Generator fan replacement	2018-04-05	2018-04-04	2018-04-05
80744	Electric generator overheating.	2017-12-22	2017-12-20	2017-12-22

Focusing on the electric generator overheating failure mode, three different experiments are performed. In these experiments, samples are organized in different ways to train, test, and validate the supervised algorithms. The samples are organized as following:

- OPT-1: the wind turbine 80284 located in the parc FRHBA is used to train and test the algorithm. The wind turbine 80744 located in the parc FRSMV is used to validate.
- OPT-2: the wind turbine 80744 located in the parc FRSMV is used to train and test the algorithm. The wind turbine 80284 located in the parc FRHBA is used to validate.
- OPT-3: the wind turbines 80744 and 80284 located in the parc FRSMV and FRHBA are used to train, test, and validation.

The table below presents in detail the samples organization.

Table 3. Inputs, outputs, and constants to calculate air density.

Experiment	Train and test samples				Validation samples			
	Mac code	Parc code	Initial date	Final date	Mac code	Parc code	Initial date	Final date
OPT-1	80284	FRHBA	2018-02-15	2018-03-06	80744	FRSMV	2017-12-10	2017-12-24
OPT-2	80744	FRSMV	2017-12-10	2017-12-24	80284	FRHBA	2018-02-15	2018-03-06
OPT-3	OPT-1 & OPT-2							

The table shows the confusion matrix metrics in percentage units:

Table 4: Pilot 1A Digital Twin Approach - Failure Detection - Error Metrics

Experiment	True Positive	False Positive	False Negative	True Negative
OPT-1 (train & test)	88,2%	0,0%	0,0%	11,8%
OPT-1 (validation)	85,3%	0,3%	13,4%	1,1%
OPT-2 (train & test)	85,6%	0,0%	0,1%	14,4%
OPT-2 (validation)	88,1%	0,0%	11,6%	0,2%
OPT-3 (train & test & validation)	87,0%	0,0%	0,0%	13,0%

The training and test process of OPT-1 and OPT-2 present a high accuracy around 99,95%. However, the validation process of OPT-1 and OPT-2 present an accuracy with modest results of 86.3% and 88.3%, respectively. This fact is interpreted as lack of failure mode information in the samples to generalise behaviour when the algorithm is trained.
Therefore, the experiment OPT-3 combines all the samples with failure mode labelled. The results exhibit excellent outcomes with an accuracy of the 100%.

The failure mode labelled and diagnosed for the three experiments are presented as a function of time in the figures below. These figures present are two signals: the labelled samples, and the predicted samples.

- Failure labelled: samples is labelled with failure mode using the information provided by the maintenance reports.
- Failure predicted: The Random Forest algorithm predicts that failure mode occurs.
- No failure predicted: The Random Forest algorithm predicts that the behaviour is normal, and no failure mode happens.
- NO failure labelled: the samples are labelled without failure mode using the information provided by the maintenance reports.

The figure below shows the validation result of OPT-1 experiment. On the one hand, the samples from wind turbine 80284 are trained and tested the Random Forest algorithm. On the one hand, the samples from wind turbine 80744, that are not used during the train and test, are shown in the figure below. The orange samples are defined

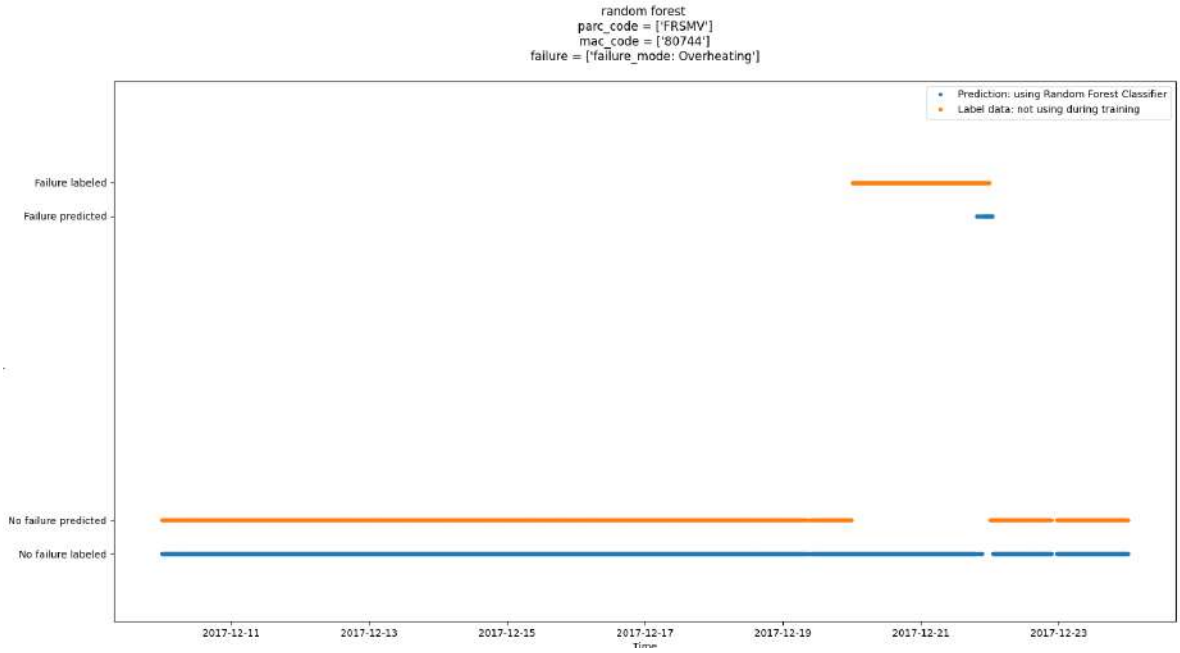


Figure 6: Validation results of experiment OPT-1, trained and test with 80284, and validated with 80744.

The figure below shows the validation result of OPT-2 experiment. On the one hand, the samples from wind turbine 80744 are trained and tested the Random Forest algorithm. On the one hand, the samples from wind turbine 80284, that are not used during the train and test, are shown in the figure below.

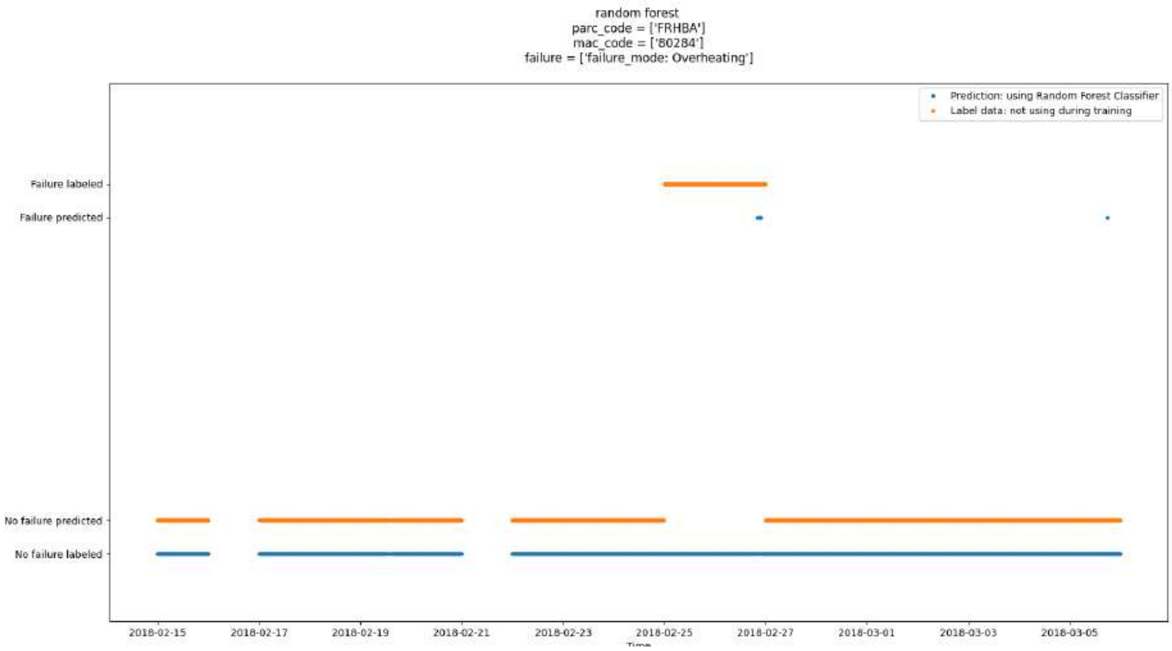


Figure 7: Validation results of experiment OPT-2, trained and test with 80744, and validated with 80284.

The figure below shows the validation result of OPT-3 experiment. This experiment uses the samples from wind turbine 80744 and 80284 to the train, test, and validation. The results are shown in the figure below. Due to all the samples.

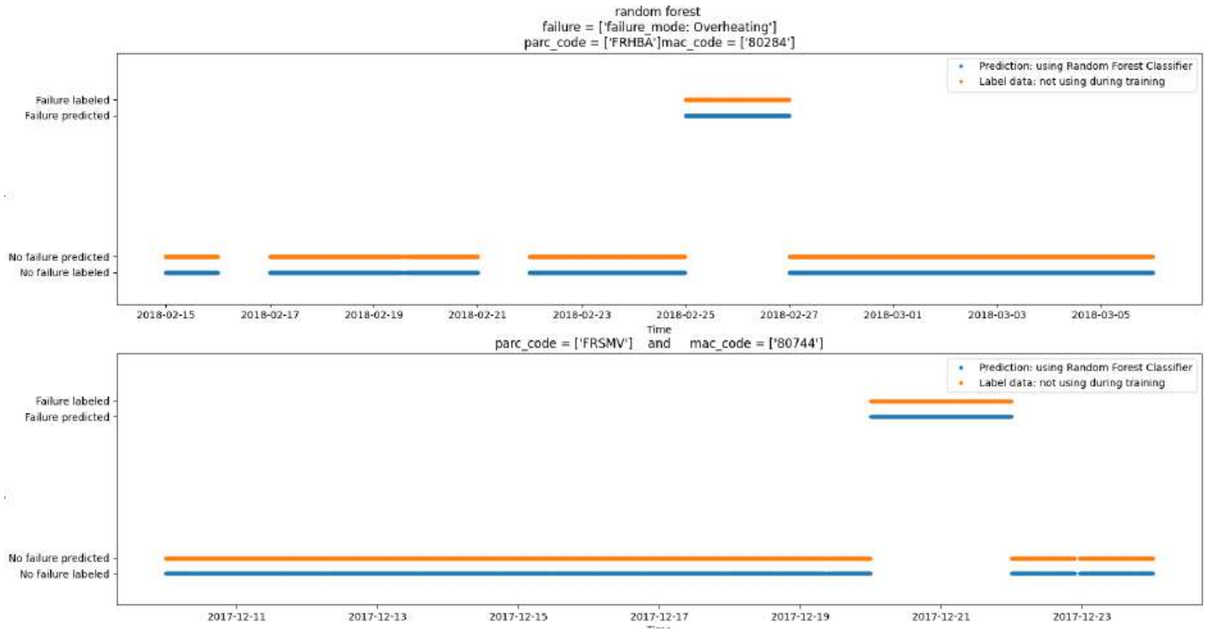


Figure 8: Validation results of experiment OPT-3, trained, tested, and validated with 80284 and 80744.

The three figures before show that failure mode predictions are temporarily grouped together. From a temporal point of view, reviewing in detail time backward and forward samples, the predictions do not fluctuate between detection and non-detection the failure mode. This fact, in addition to the favourable prediction results, makes it reasonable to conclude that the new algorithm based on Random Forest algorithm is operating adequately.

Regarding the validation of the RUL estimation tool, real failure labelled data was used to validate the tool. More in detail, in wind farm Le Champ Vert (FRCVE) it was a IGBT rack replacement labelled in wind turbines 80501 and 80505. So, it is decided to study in detail the behavior of three wind turbines installed in this wind farm: 80499 (no failure), 80501 (rack replacement 06/01/2016-07/01/2016, a period before the availability of real data) and 80505 (rack replacement 08/06/2020-07/07/2020), applying the methodology to calculate the life consumption.

Temperatures in the diode and the IGBT of wind turbine 80501, considering a period of maximum power, are shown in Figure AAB. The behavior in terms of temperature is similar in the three wind turbines.

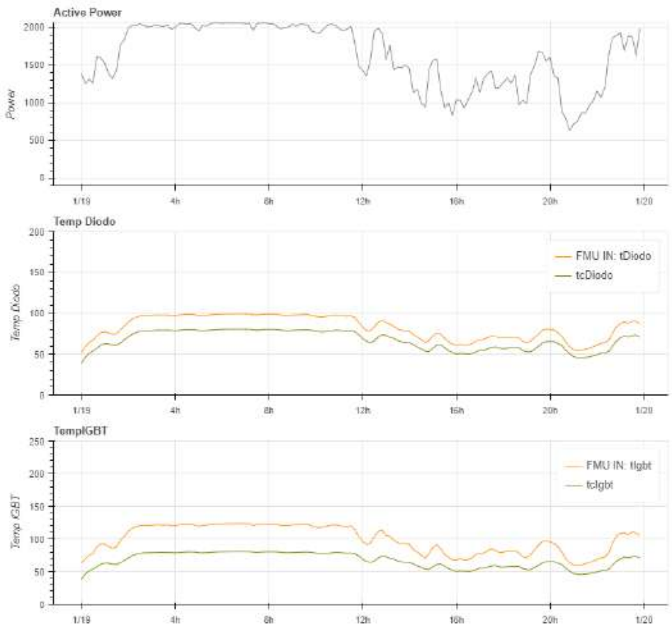
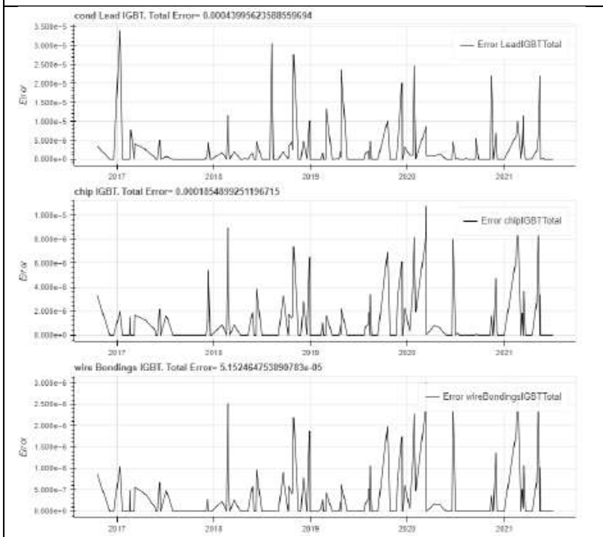
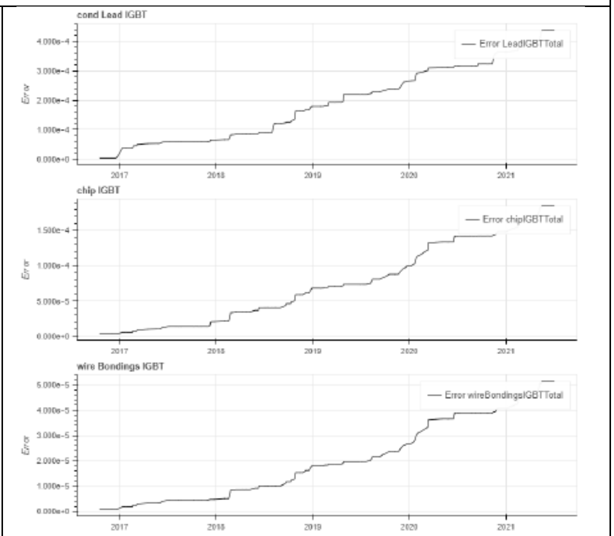


Figure 9: Offline results for turbine 80501

The daily life consumption relating to the working duty along the operation years (2016 - 2022) is shown in Table 5 left columns, while in right columns the cumulative life consumption is shown.

Table 5: Percentage of loss of life in conductor lead, chip and wire bonding (daily/cumulative)

<table>
<tr><td colspan="2">FRCVE_80499</td></tr>
<tr><td></td><td></td></tr>
<tr><td colspan="2">FRCVE_80501</td></tr>
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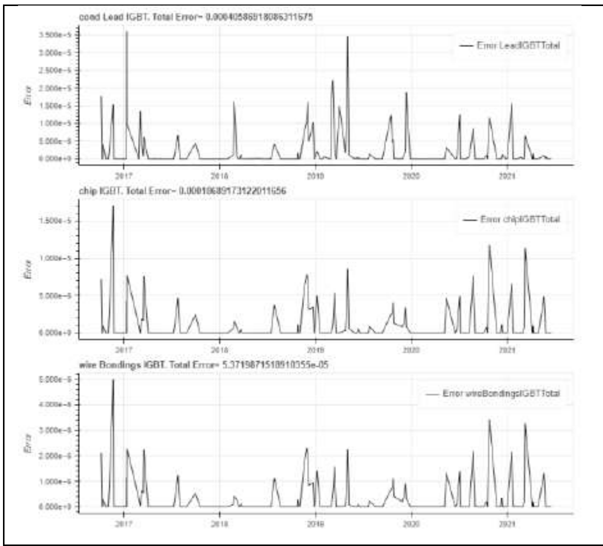
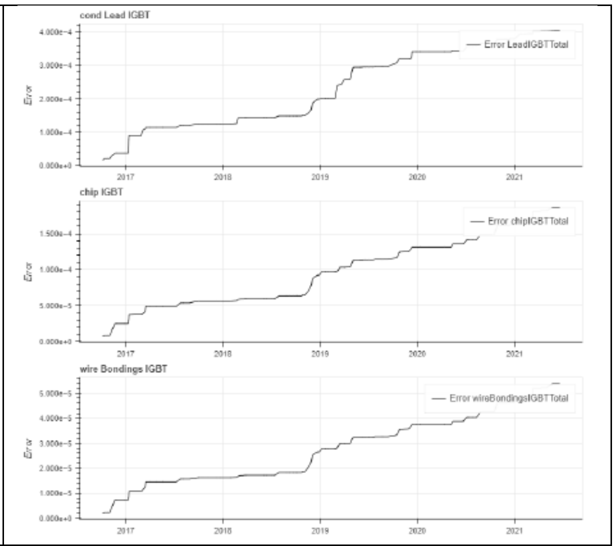
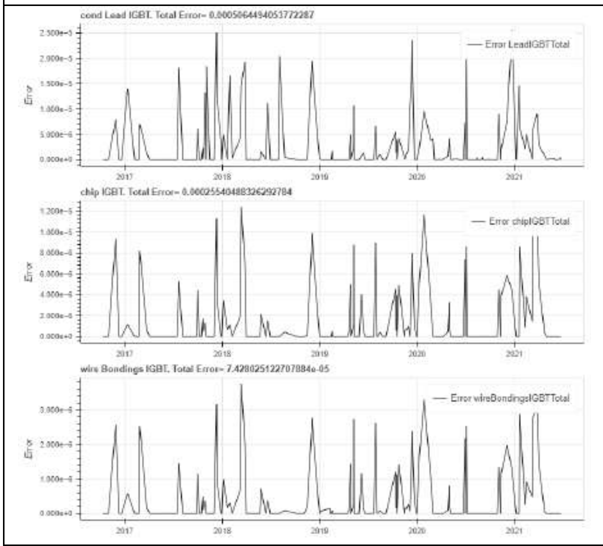
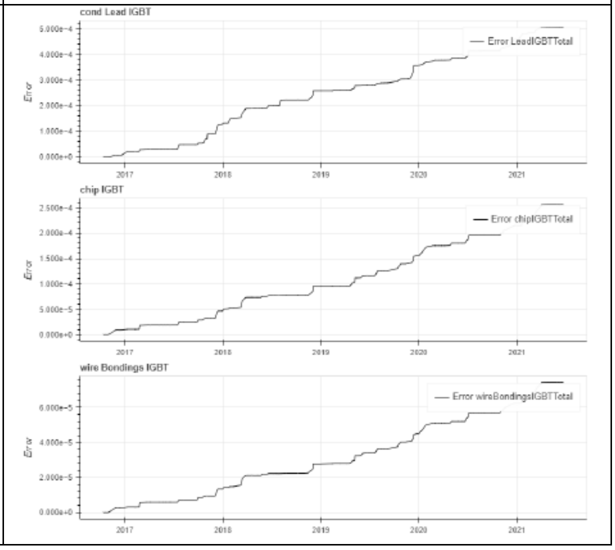
	
FRCVE_80505	
	

In Figure 10, the cumulative loss of life is shown in the same graphic. It can be seen that the wind turbine with the labelled change of IGBT rack in 2020 year (FRCVE 80505) has a higher loss of life than the other two wind turbines.

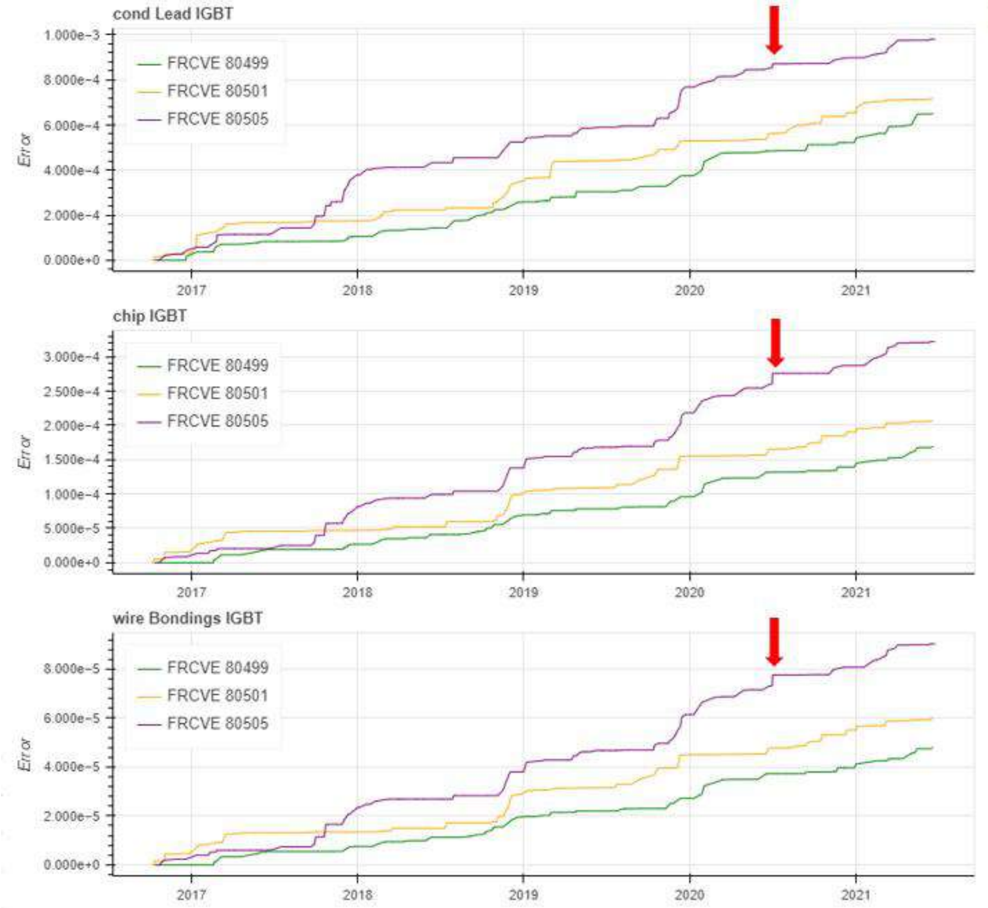


Figure 10: Comparison of cumulative loss of life in conductor lead, chip and wire bonding

However, although there are available data of almost 5 years (2016 - 2021), there are a lot of days with no data:

- data_FRCVE_80499: 18/10/2016 – 06/07/2021 (1722 días) à only data of 168 days
- data_FRCVE_80501: 06/10/2016 – 28/06/2021 (1726 días) à only data of 159 days
- data_FRCVE_80505.csv: 12/10/2016 – 01/07/2021 (1723 días) à only data of 187 days

So, a correction has been made with the intention of considering this fact in the calculation of the accumulate life consumption.

Total_Error	wireBondingIGBT	CondLeadIGBT	ChipIGBT
FRCVE_80499	0,000048	0,000652	0,000169
FRCVE_80501	0,000060	0,000718	0,000208
FRCVE_80505	0,000090	0,00098	0,000322

Extrapolation to the total number of days

Total_Error	wireBondingIGBT	CondLeadIGBT	ChipIGBT
FRCVE_80499	0,000492	0,006683	0,001732
FRCVE_80501	0,000651	0,007794	0,002258
FRCVE_80505	0,000829	0,009030	0,002967

Extrapolation to the total number of days from commissioning (4783)

Total_Error	wireBondingIGBT	CondLeadIGBT	ChipIGBT
FRCVE_80499	0,001367	0,018563	0,004811
FRCVE_80501	0,001805	0,021599	0,006257
FRCVE_80505	0,002302	0,025066	0,008236

Figure 11: Real loss of life correction

Considering that the expected lifetime of a converter is 20 years, the loss of life in 4 years (or 12 years) is not realistic in absolute terms, although in comparison terms the results are according to the reality. It must be also considered that the methodology has been applied using SCADA data every 10 minutes. The model would have been more accurate with higher frequency data.

Regarding the processing capability, the full processing pipeline has been implemented (see D6.2) and is able to run on a standard server. The training part and dockerisation of the Digital Twin in Matlab showed a high consumption of RAM and CPU. However, once it is dockerised the execution phase is significantly less computationally expensive and can be run in any standard server with 4CPUs and 16GB RAM.

Finally, to calculate the Maintenance Cost Reduction and Availability Increase the following assumptions were made:

- A generator stator fan failure happens 0,4 times in the lifetime of a wind turbine (considering 25 years lifetime). This is based on the from the D4REL project that stated that 0,1 generator fails per turbine per year. of those 16% is linked to the stator[1].
- Based on the results of the data analytics toolbox, we assume 10% of generator stator fan failures can be detected thanks to the developed Hybrid Digital Twin and Failure detection data analytics toolbox. Although the tool was able to detect 100% (2/2) of the labelled failures we assume a safety factor due to other unlabelled failures that we might have missed and due to the generalisation capacity limitation explained previously.
- Cost of generator replacement:
    - 3 weeks downtime cost: 2 MW machine * 30% capacity factor * 21 days *24h = +/- 300 MWh => at 70 euro/MWh => 21 k€

[1] Deliverable 1.1 Wind Turbine Generator Systems Failures Probabilities and Mechanisms, D4REL , https://www.d4rel.nl/.

- 3 days work to replace the generator: 6k€
- 50k€ for the crane
- 50k€ for the generator
- Total cost of 127 k€

Hence, per wind turbine we can prevent 5k€ per WT during its lifetime. Therefore, considering a fleet of 1000 WT we can prevent 5M€ of maintenance costs.

Regarding the availability, we could prevent 10% of 1300 weeks of operation fleetwide which corresponds to an availability increase of 0.01%, which is negligible.

2.2.1.2 Data driven approach

Table 6: LLUC-1A-01-KPIs evaluation- Data driven approach

KPI #	Description	Target Value	Actual Value	Comments
1	Modelling quality	3%	See **¡Error! No se encuentra el origen de la referencia.**	This goal can be considered accomplished given that the performance on all signals is close to or surpasses the target value and the fact that steady-state and transient are modelled together.
2	Integration	1	1	The different apps of the pipeline are well integrated. The integration has been tested thoroughly. The IDS development has been completed, tests have been done. The data analytics pipeline and the IDS connectors can work together.
3	Fault Detection	Compared to the current failure detection the speed should improve with at least 25%, while keeping false positives below 10%	Accomplished	False positives can be held bellow the false positive threshold of 10% (see part KPI 3).
4	Processing Capability	Full processing chain for a farm should be able to run on a standard server.	Accomplished	The pipeline was validated on a standard server (see part KPI 4).

5	Maintenance costs reduction	10-20%	Accomplished	The cost reduction surpasses the 20% threshold (see part KPI 5).
6	Availability increase	2-5%	Accomplished	The availability of the turbines increases by more than 2% when the data analytics pipeline is used.

To assess whether the KPIs are achieved, the pipeline is tested on data from 6 wind farms available in the ENGIE Senvion historical batch, e.g. FRCVE (Senvion MM82), FRPHA (Senvion MM82), FRHBA (Senvion MM82), FRHBO (Senvion MM82), FRBOU (Senvion MM82) and FRECH (Senvion MM92).

KPI 1: Modelling quality

KPI description:

Accuracy of the predicted value compared to the real value under healthy operating conditions using the Mean Absolute Percentage Error (MAPE). Target value = 3% and threshold value = 5%.

Results:

The accuracy results presented here are for healthy steady-state and transient data combined. Improvements in the methodology have made it possible to model the steady-state and the transient behaviour of the wind turbines accurately with a single model. This means that the distinction between the two is no longer relevant. This is a major improvement over the original KPI.

Figure 12 shows that the MAPE of the Normal Behaviour Model (NBM) for wind farm FRCVE (Senvion MM82) is slightly higher than the target value of 3%, but very close. Figure 13 indicates that the MAPE for the FRPHA wind farm is lower than 3% for all the signals. Figure 14 and Figure 15 tell the same story for respectively wind farms FRHBA and FRBOU. Figure 16 shows that the MAPE on the wind farm FRHBO is slightly larger than 3%. Figure 17 shows the results for the wind farm FRECH. This wind farm consists of turbines of the type Senvion MM92. The MAPE (%) is for all signals substantially lower than 3%. For all turbines the MAPE is smaller than the threshold value of 5%.

Conclusion:

Based on these results it can be concluded that KPI 1 is achieved.

Signal name	TempGenBearing_1 (avg)	TempGenBearing_2 (avg)	TempStatorWind (avg)
CV1	3.17	2.74	2.36
CV2	6.87	3.02	4.48
CV3	3.07	2.37	2.53
CV4	3.34	2.44	2.46
CV5	2.84	4.47	3.58
ALL	3.86	3.01	3.08

Figure 12: MAPE (%) of Normal Behaviour Model for wind farm FRCVE.

Signal name	TempGenBearing_1 (avg)	TempGenBearing_2 (avg)	TempStatorWind (avg)
PH1	2.45	2.78	3.05
PH2	2.00	2.40	2.63
PH3	2.94	3.08	2.74
PH4	2.75	3.80	2.29
PH5	1.87	2.15	2.73
PH6	2.59	2.13	2.99
ALL	2.43	2.72	2.74

Figure 13: MAPE (%) of Normal Behaviour Model for wind farm FRPHA.

Signal name	TempGenBearing_1 (avg)	TempGenBearing_2 (avg)	TempStatorWind (avg)
HB1	2.18	1.59	2.02
HB2	2.61	1.71	2.16
HB3	2.07	1.94	2.02
HB4	2.43	2.30	2.61
HB5	1.97	3.15	2.50
HB6	1.44	1.67	1.83
ALL	2.12	2.06	2.19

Figure 14: MAPE (%) of Normal Behaviour Model for wind farm FRHBA.

Signal name	TempGenBearing_1 (avg)	TempGenBearing_2 (avg)	TempStatorWind (avg)
BO1	2.39	5.14	4.42
BO2	1.98	2.32	2.80
BO3	4.32	2.46	2.88
BO4	2.67	1.98	2.41
BO5	2.19	3.40	4.35
BO6	1.88	2.52	2.41
ALL	2.57	2.97	3.21

Figure 15: MAPE (%) of Normal Behaviour Model for wind farm FRBOU.

Signal name	TempGenBearing_1 (avg)	TempGenBearing_2 (avg)	TempStatorWind (avg)
HBO1	4.23	4.21	3.00
HBO2	3.78	6.87	3.53
HBO3	3.44	2.54	2.61
HBO4	3.59	3.39	2.95
ALL	3.76	4.25	3.02

Figure 16: MAPE (%) of Normal Behaviour Model for wind farm FRHBO.

Signal name	TempGenBearing_1 (avg)	TempGenBearing_2 (avg)	TempStatorWind (avg)
ECH1	1.76	1.52	3.11
ECH2	1.63	1.66	1.98
ECH3	1.42	1.45	1.84
ECH4	2.86	2.10	2.18
ECH5	1.61	2.75	3.08
ECH6	4.39	2.24	3.44
ECH7	1.10	2.04	1.94
ECH8	1.11	1.57	1.83
ALL	1.98	1.92	2.42

Figure 17: MAPE (%) of Normal Behaviour Model for wind farm FRECH.

KPI 2: Integration

KPI description:

Metric targeted at the validation of the fact that the tools of this pilot are able to work together.

Results:

The different sub-apps of the VUB data analytics pipeline have been thoroughly tested in an integration test (this was shown during multiple demos to the other partners of PLATOON). The test showed that the different sub-apps can work together with no issues. The VUB data analytics pipeline is also able to use the output of the TECN digital twin as an input signal. Figure 18 shows the output of the SCADA_Data_Cleaner for the turbine BO1. The output contains the signals "Simulated stator winding temperature fleet" and "Simulated stator winding temperature BO1". These signals are preprocessed versions of the simulated signal generated by the TECN digital twin. The simulated signal has been preprocessed, so that it can be used in the next steps of the VUB data analytics pipeline. This proves that both pipelines (e.g. the TECN digital twin and the VUB data analytics pipeline) are integrated. The interoperability with the IDS connector has also been tested. The pipeline can use the data that is being delivered by the VUB IDS consumer. The data that is produced by the pipeline can also be send back to ENGIE using the VUB IDS producer. The integration between the TECN digital twin and the VUB data analytics pipeline has been tested and is successful.

```
Index(['TempGenBearing_1 (avg) fleet median', 'TempGenBearing_1 (avg) B01',
       'TempGenBearing_2 (avg) fleet median', 'TempGenBearing_2 (avg) B01',
       'TempStatorWind (avg) fleet median', 'TempStatorWind (avg) B01',
       'TempConvInlet (avg) fleet median', 'TempConvInlet (avg) B01',
       'TempGearbBear_1 (avg) fleet median', 'TempGearbBear_1 (avg) B01',
       'TempGearbBear_2 (avg) fleet median', 'TempGearbBear_2 (avg) B01',
       'TempGearbInlet (avg) fleet median', 'TempGearbInlet (avg) B01',
       'TempRotorBearing (avg) fleet median', 'TempRotorBearing (avg) B01',
       'Simulated stator winding temperature fleet median',
       'Simulated stator winding temperature B01', 'active power fleet median',
       'active_power B01', 'generator_speed fleet median',
       'generator_speed B01', 'nacelle_temperature fleet median',
       'nacelle_temperature B01', 'outside_temperature fleet median',
       'outside_temperature B01', 'rotor_speed fleet median',
       'rotor_speed B01', 'torque fleet median', 'torque B01',
       'wind_speed fleet median', 'wind_speed B01',
       'gearbox_speed fleet median', 'gearbox_speed B01',
       'curtailed fleet median', 'curtailed B01', 'op_cond fleet median',
       'op_cond B01',
       'Unhealthy data: Failure: Generator bearing replacement B01',
       'Unhealthy data: Failure: Generator fan replacement B01',
       'Unhealthy data: Failure: IGBT fan replacement B01',
       'Unhealthy data: Failure: IGBT rack replacement B01',
       'Unhealthy data: Failure: Rotor brush high temperature B01',
       'Unhealthy data: Failure: Slipring replacement B01', 'abs_op_cond B01'],
      dtype='object', name='Windturbine name')
```

Figure 18: Output SCADA_Data_Cleaner that contains the generator stator winding temperature simulated by the TECN digital twin.

Conclusion:

Based on these results it can be concluded that most elements of the KPI have been achieved. A KPI score = 1 can be assigned.

KPI 3: Fault detection

KPI description:

Anomaly detection speed + accuracy (false vs true positive). The accuracy is expressed using a confusion matrix. For the speed this is expressed in time to catastrophic failure. Compared to the current failure detection the speed should improve with at least 25%, while keeping false positives below 10%

Results:

Constructing a confusion matrix on data from real wind farms is not a trivial task. There are several unknowns. When did the damage that eventually resulted in the failure start? Was the problem after the replacement immediately fixed or did it persist for while? Is the date of the replacement exact or is there some margin of error? Is the list of failures complete? This makes determining what a true/false positive/negative is not a straightforward task. Some assumptions will need to be made.

- True positive (TP): is when the health of the signal that is relevant for the failure has degraded to “bad” around the time of the replacement or failure. Some failures form slowly over time. This means that the signal health can degrade to bad a long time before the replacement or failure actually happens. The bad health can also persist for a short while after the failure or replacement. This can be due to an imprecise replacement date, or the run-in of a new component or a maintenance handling that did not resolve the issue at the first attempt. It is however important that the bad health classification improves to “mediocre” or “good” not to long after the replacement.
- True negative (TN): is when the health of the signal improves to “mediocre” or “good” not to long after a failure. It needs to be taken into account that there can be some delay in the improvement. This can be the result of an imprecise replacement date, or the run-in of a new component or a maintenance handling that did not resolve the issue at the first attempt.
- False positive (FP): If after the replacement or failure there is no indication that the health of the signal has improved.
- False negative (FN): If prior to the replacement or failure there is no clear bad health classification for the relevant signal.

Table 7: Confusion matrix generator bearing replacements

		Failure	
		T	F
Anom	T	3	0
	F	1	4

Table 8: Confusion matrix generator fan replacements.

		Failure	
		T	F
Anom	T	3	1
	F	0	2

Table 9: Confusion matrix rotor brush high temperature failure.

		Failure	
		T	F
Anom	T	4	1
	F	1	4

Table 7 shows the confusion matrix for the generator bearing replacements. The metrics for this failure are: accuracy = 0.88, precision = 1.00, recall = 0.75 and F1 = 0.86. Table 8 shows the confusion matrix for the generator fan replacements. The metrics for this failure are: accuracy = 0.83, precision = 0.75, recall = 1.00 and F1 = 0.86. Table 9 shows the confusion matrix for the rotor brush high temperature failures. The metrics are: accuracy = 0.80, precision = 0.80, recall = 0.80 and F1 = 0.80.

The detection speed is defined as the time between the first detection in the cluster of detections that can be associated with the replacement or failure and the failure itself. 66% of the detected generator bearing replacements were detected at least one month before the replacement. 66% of the detected generator fan replacements were detected at least 1 month in advance. 75% of the detected rotor brush high temperatures were detected at least 1 month in advance.

The KPI determines that the false positives need to be lower than 10%. The confusion matrices shown above focus strongly on a window of data around the failures. This is however insufficient to get an idea of the overall number of false positives the pipeline generates. For this reason a different methodology is used. The false positives are calculated as the percentage of observations that are considered "bad health" for turbines that did not experience any known relevant replacements or failures (i.e. generator bearing replacements, generator fan replacements or rotor brush high temperature failures). For each signal the median of these percentages is calculated. To achieve this KPI the median needs to be below 10%. Table 10 shows that this target is achieved for 2 of the 3 signals. For TempGenBearing_1 (avg) the median is slightly higher than 10%. The results for all signals combined give a median lower than 10%.

Table 10: Percentage of observations classified as bad health for turbines that have not experienced any relevant failures during the observation periods.

Wind farm	Wind turbine name	TempGenBearing_1 (avg)	TempGenBearing_2 (avg)	TempStatorWind (avg)
FRCVE	CV1	2.79	2.79	13.44
FRCVE	CV4	8.44	8.31	5.52
FRPHA	PH1	26.64	40.87	2.86
FRHBO	HBO3	12.07	15.01	1.05
FRHBO	HBO4	10.47	21.1	9.36
FRBOU	BO2	15.39	3.77	10.79
FRBOU	BO3	5.66	5.22	8.24
FRBOU	BO6	8.7	3.45	7.7
FRECH	ECH1	0.14	27.63	0.14
FRECH	ECH2	8.35	3.02	1.58
FRECH	ECH3	1.63	49.27	0
FRECH	ECH4	14.57	4.76	27.27
FRECH	ECH5	40.33	14.63	0
FRECH	ECH6	15.4	19.57	33.38
FRECH	ECH7	4.6	17.55	3.45
FRECH	ECH8	25.04	1.15	1.58
FRHBA	HB1	10.42	21.47	7.18
FRHBA	HB2	14.02	3.34	7.35
FRHBA	HB4	1.95	7.47	1.82
Median		**10.42**	**8.31**	**5.52**

Lastly, the KPI also determines that compared to the current failure detection the detection speed should improve (and preferably with 25%). To assess whether this KPI was achieved, the following analysis is done. For each failure is determined which detector (old or new) detected the failure first. The detector that detected it first gets a score of 1 for this failure. In the end the mean is taken of the scores for the new detector and multiplied by 100, to get a result in percent. The Table 11 shows that 50% of the generator bearing replacement cases were detected first by the new detector. Table 12 shows that 66% of the generator fan replacements were detected first by the new detector. Table 13 shows that 60% of the rotor brush high temperature failures are detected first by the new detector. This means that for all three cases the KPI of 25% improvement is achieved.

Table 11: Improvement new detector over old detector.

Turbine	Failure	Date	Old detector	New detector
CV5	Generator bearing replacement	6/07/2017	0	0
PH5	Generator bearing replacement	4/07/2017	0	0
HB3	Generator bearing replacement	31/10/2019	0	1

HBO2	Generator bearing replacement	19/10/2018	0	1
Improvement	50%			

Table 12: Improvement new detector over old detector.

Turbine	Failure	Date	Old detector	New detector
PH6	Generator fan replacement	11/01/2017	0	1
HB5	Generator fan replacement	4/04/2018	0	1
BO1	Generator fan replacement	21/12/2018	0	0
Improvement	66%			

Table 13: : Improvement new detector over old detector.

Turbine	Failure	Date	Old detector	New detector
CV2	Rotor brush high temperature	29/09/2019	0	1
PH2	Rotor brush high temperature	29/09/2019	0	1
PH3	Rotor brush high temperature	28/06/2020	0	0
HBO4	Rotor brush high temperature	14/06/2018	0	1
BO1	Rotor brush high temperature	21/04/2020	0	0
Improvement	60%			

Conclusion:

Based on the results it can be concluded that the KPI has been achieved.

4: Processing Capability

KPI description:

There are two aspects being tested in this KPI. The first is the speed at which one complete data analysis by the complete pipeline can be done. The second is the number of turbines that are feasible to be analysed using the approach.

Results:

To test whether it is feasible to run the whole pipeline on standard server equipment, tests are conducted on data from three different wind farms (with different sizes). The wind farms are: FRHBO (4 wind turbines), FRBOU (6 wind turbines) and FRHBO+FRBOU (10 turbines). The last wind farm is an artificial one composed of the data from FRHBO and FRBOU. This new dataset can then be used as a proxy for larger wind farms, which should allow us to make an assessment of how well the pipeline scales to larger datasets.

The tests are run on standard server equipment: a VM running Ubuntu 20.04 LTS with 20 cores assigned from an Intel(R) Xeon(R) Gold 6130 CPU @ 2.10GHz and 100 GB RAM. To validate the KPI a monitoring script is used that registers the user and system CPU time and also the RAM consumption by the process(es) that are created by the script. Since the different applications of the pipeline are run sequentially, meaning first the SCADA_Data_Cleaner, then the Anomaly_Detection, etc… each application demands resources sequentially. This means that the RAM consumption of the different applications should not be added up to get an idea of the RAM requirements of the pipeline. The CPU time on the other hand must be summed to get the CPU time of the pipeline.

SCADA_Data_Cleaner

Figure 19, Figure 20 and Figure 21 show the resource consumption of the SCADA_Data_Cleaner for the processing of the data for resp. FRHBO, FRBOU and FRHBO+FRBOU. For FRHBO (4 turbines) the total CPU time is 103.16 s and the maximum RAM consumption is 3269.53 MB. For FRBOU (6 turbines) it is 141.07 s and 5290.18 MB resp.. And for the FRHBO+FRBOU (10 turbines) it is 213.51 s and 7440.78 MB resp.. This indicates that the SCADA_Data_Cleaner can easily be run on standard server equipment. Scalability is also not an issue.

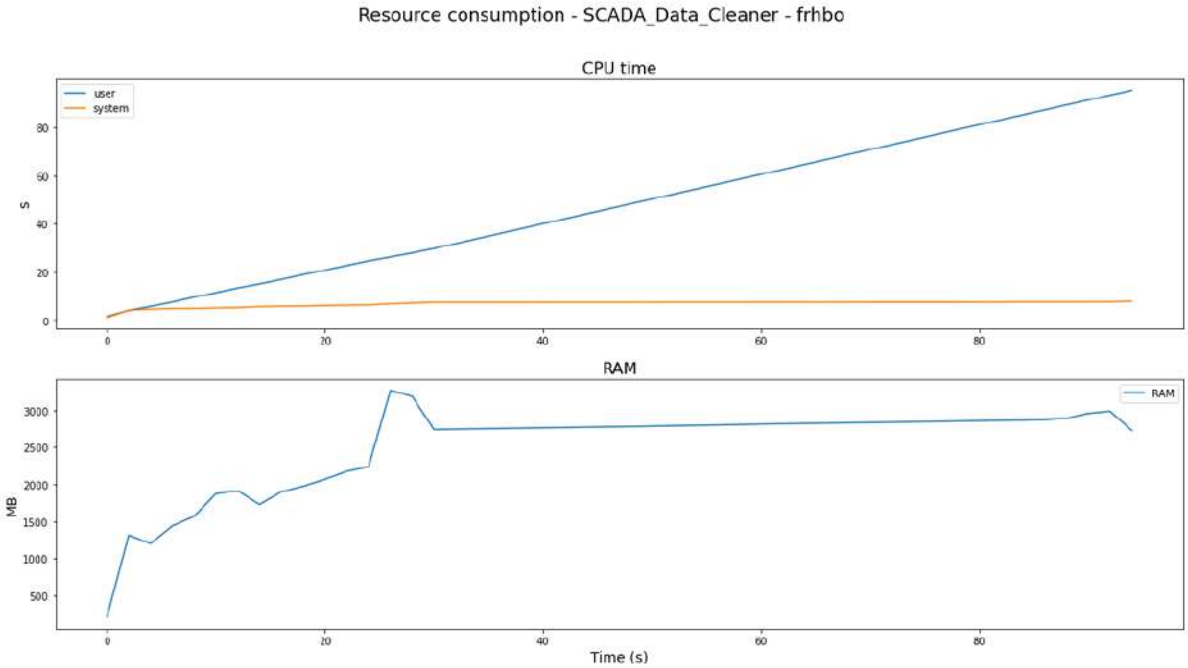


Figure 19: Resource consumption by SCADA_Data_Cleaner for processing FRHBO data.

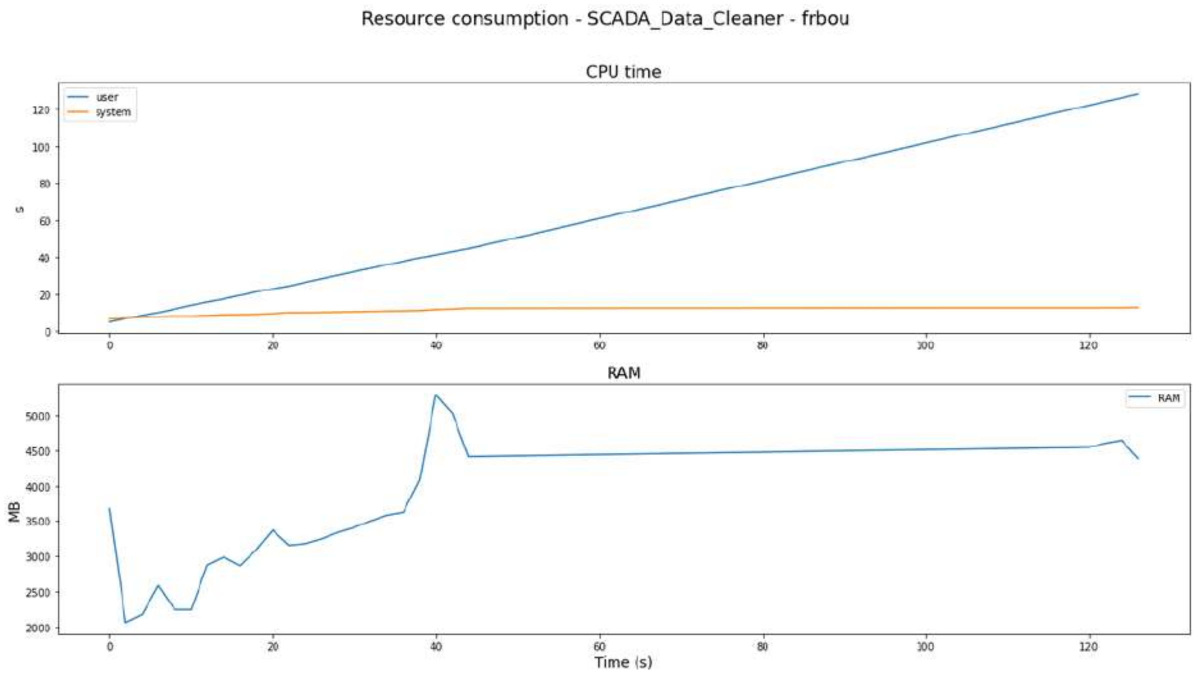


Figure 20: Resource consumption by SCADA_Data_Cleaner for processing FRBOU data.

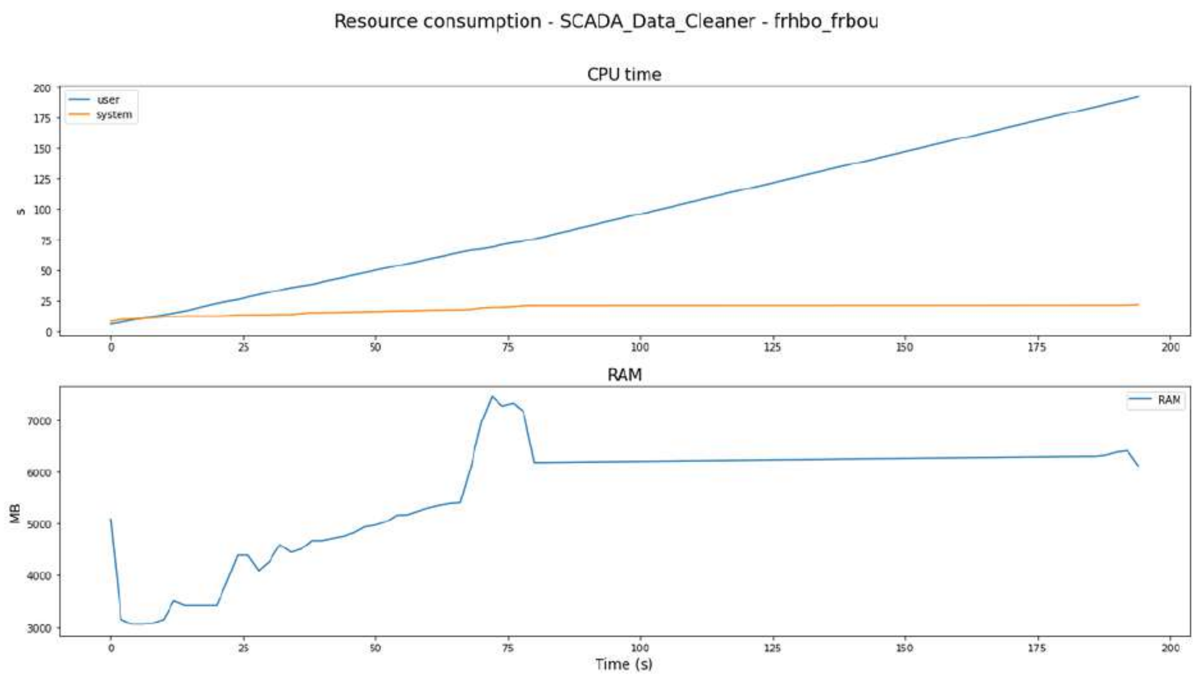


Figure 21: Resource consumption by SCADA_Data_Cleaner for processing FRHBO+FRBOU data.

Anomaly_Detection

Figure 22, Figure 23 and Figure 24 show the resource consumption of the Anomaly_Detection (if the models need to be trained) for the processing of the data for resp. FRHBO, FRBOU and FRHBO+FRBOU. For FRHBO (4 turbines) the total CPU time is 18669.59 s (divided over 20 cores, which equals a run time of 933.48 s on a 20-core CPU) and the maximum RAM consumption is 3972.05 MB. For FRBOU (6 turbines) the total CPU time is 40666.01 s (divided over 20 cores, which equals a run time of 2033.30 s on a 20-core CPU) and RAM consumption is 4584.17 MB resp.. And for the FRHBO+FRBOU (10 turbines) the total CPU time is 94566.45 s (divided over 20 cores, which equals a run time of 4728.32 s on a 20-core CPU) and RAM consumption is 5594.29 MB resp.. This indicates that the Anomaly_Detection can easily be run on standard server equipment. Scalability is also not an issue.

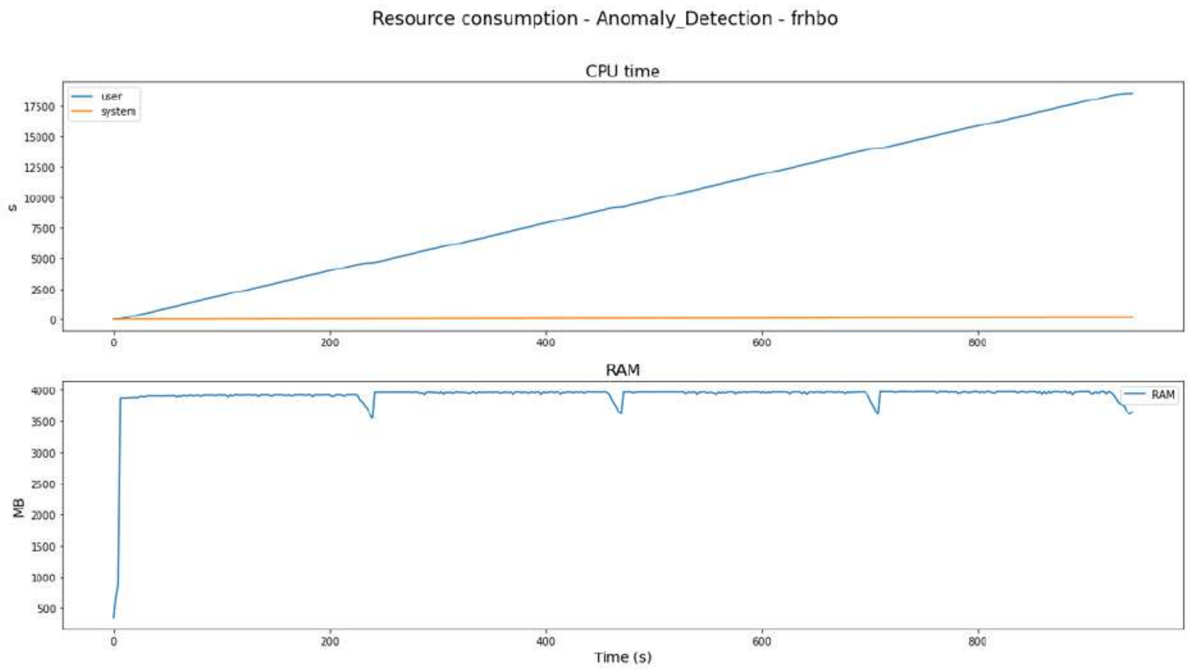


Figure 22: Resource consumption by Anomaly_Detection for processing FRHBO.

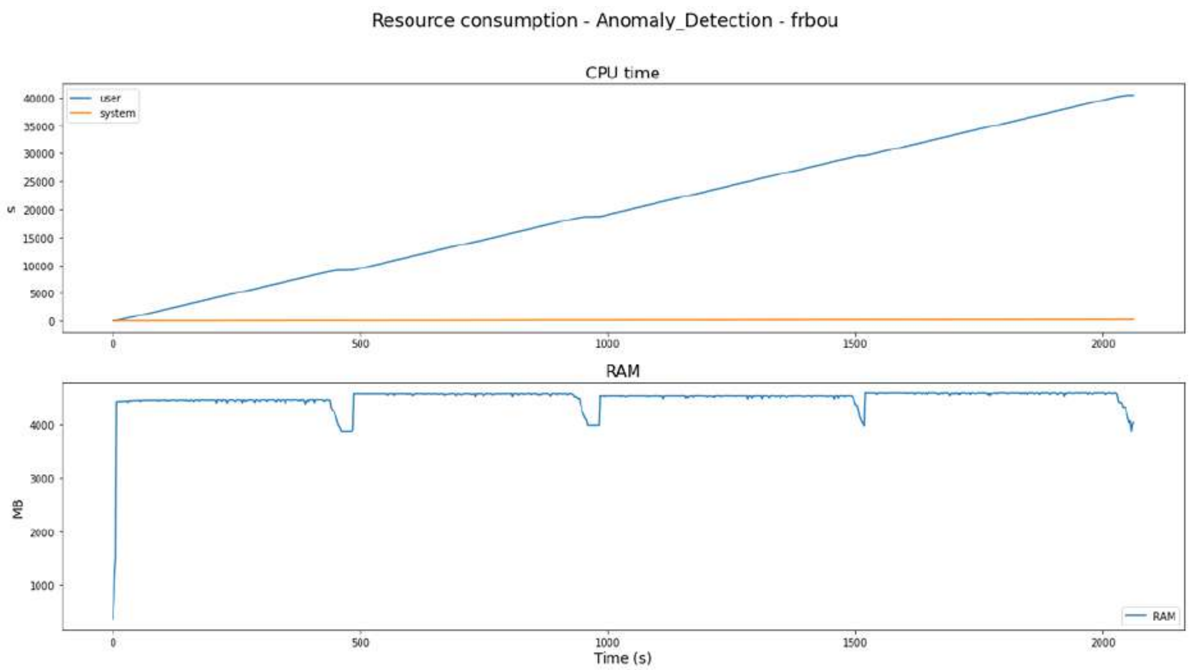


Figure 23: Resource consumption by Anomaly_Detection for processing FRBOU.

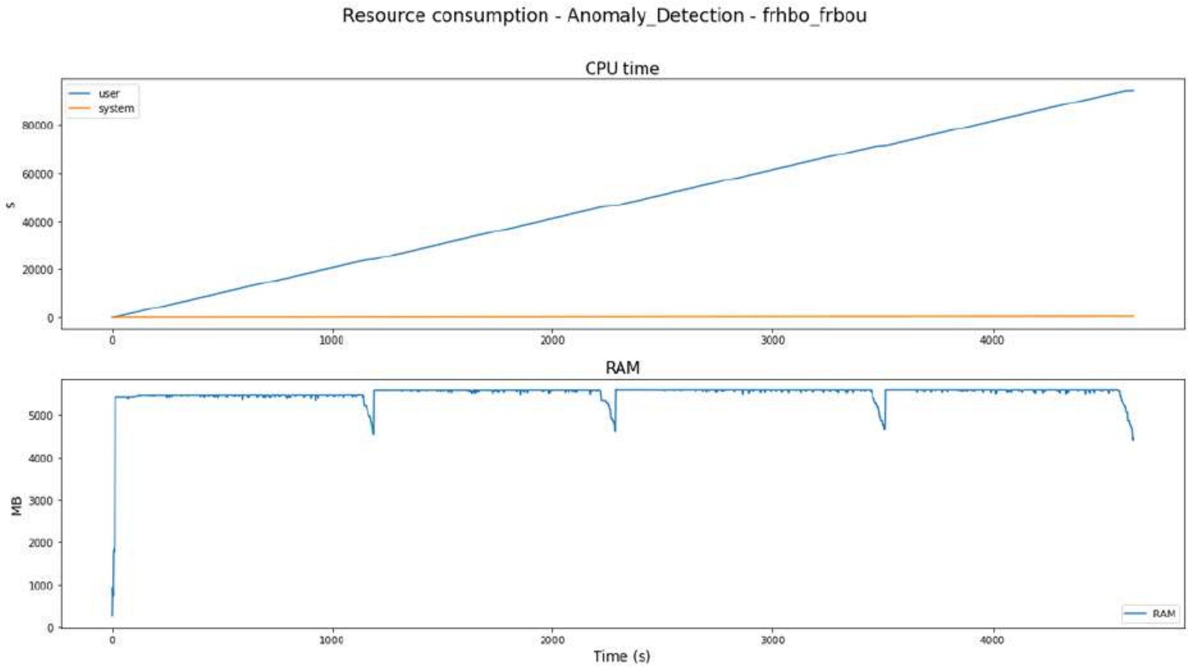


Figure 24: Resource consumption by Anomaly_Detection for processing FRHBO+FRBOU.

Failure_Diagnosis

The Failure_Diagnosis app runs only for a very short time (< 1 s) and consumes only a small amount of RAM (< 200 MB) for all three datasets. This makes the contribution of this app to the resource consumption by the whole pipeline irrelevant.

Root_Cause_Identifier

Figure 22, Figure 23 and Figure 24 show the resource consumption of the Root_Cause_Identifier for the processing of the data for resp. FRHBO, FRBOU and FRHBO+FRBOU. For FRHBO (4 turbines) the total CPU time is 23.65 and the maximum RAM consumption is 143.91 MB. For FRBOU (6 turbines) the total CPU time is 39.86 s and RAM consumption is 160.22 MB resp.. And for the FRHBO+FRBOU (10 turbines) the total CPU time is 66.80 s and RAM consumption is 193.41 MB resp.. This indicates that the Root_Cause_Identifier can easily be run on standard server equipment. Scalability is also not an issue.

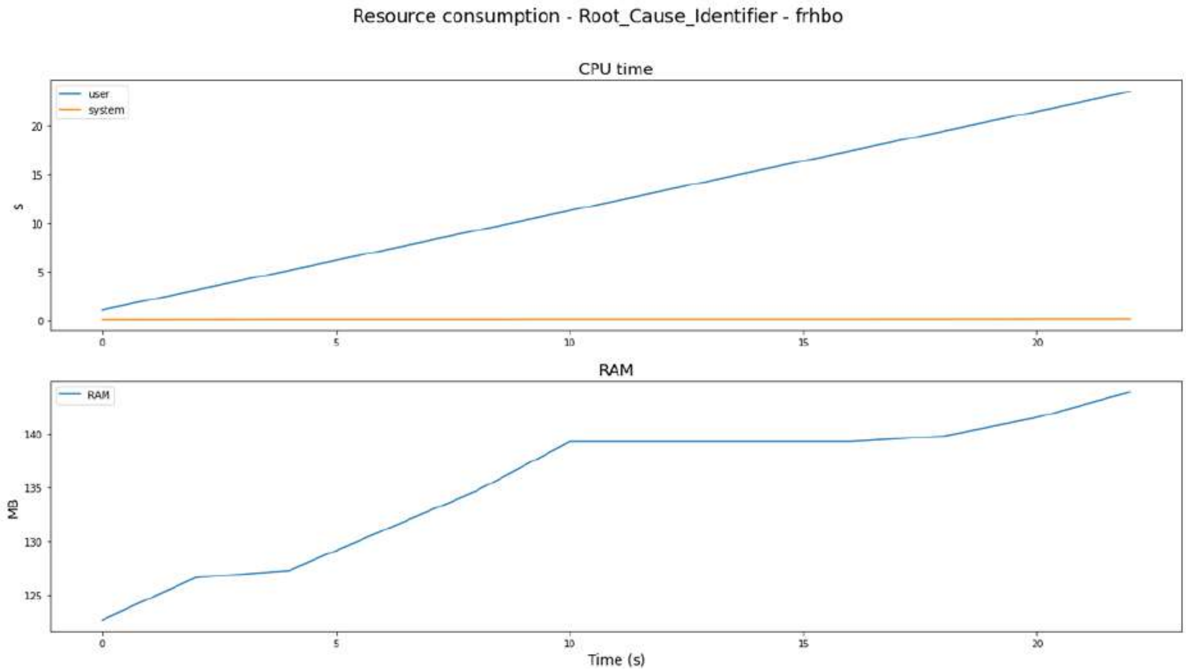


Figure 25: Resource consumption by Root_Cause_Identifier for processing FRHBO.

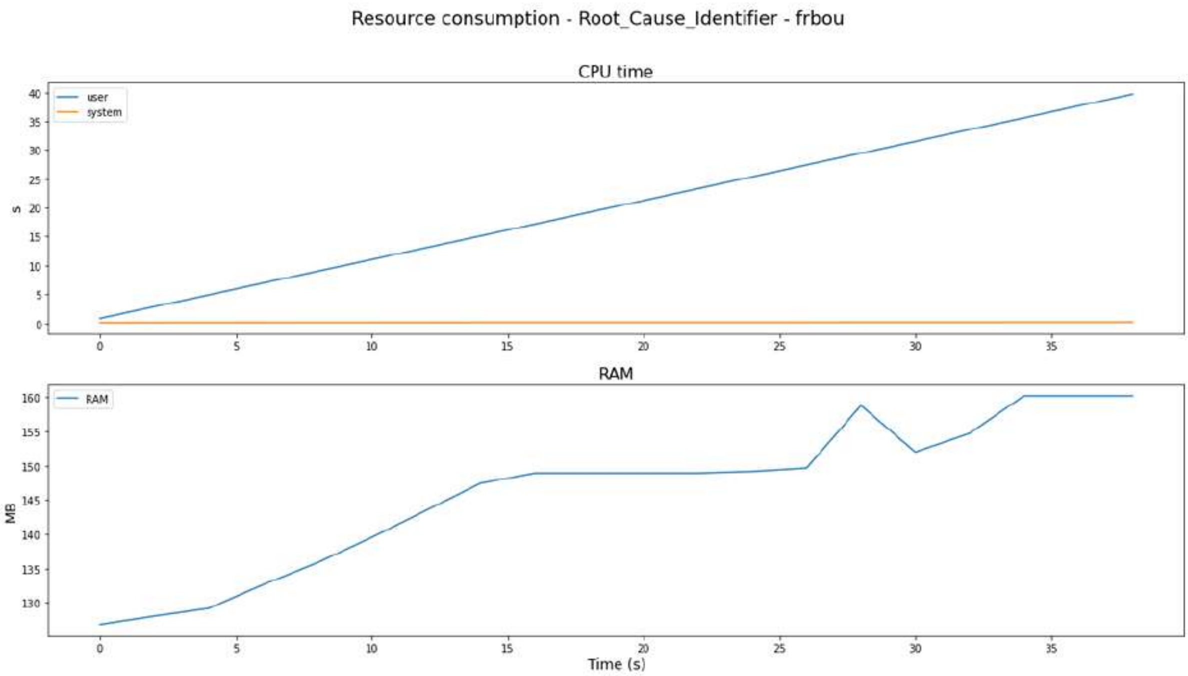


Figure 26: Resource consumption by Root_Cause_Identifier for processing FRBOU.

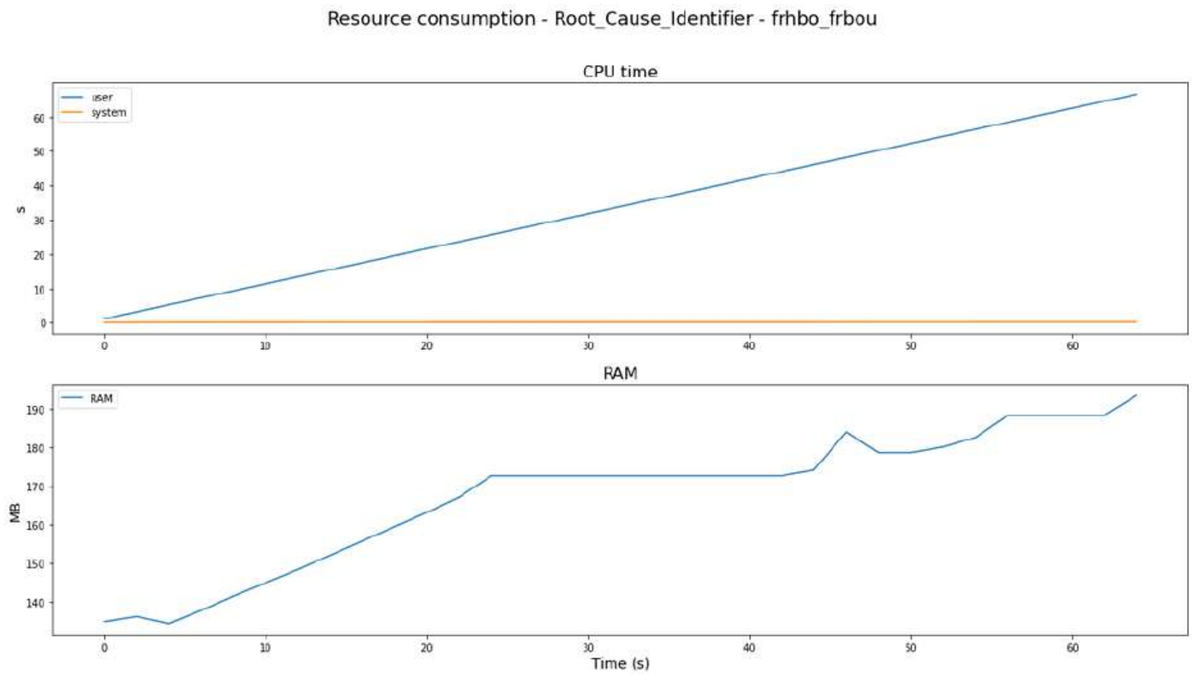


Figure 27: Resource consumption by Root_Cause_Identifier for processing FRHBO+FRBOU.

Dashboard_Preparation

Figure 28, Figure 29 and Figure 30 show the resource consumption of the Dashboard_Preparation for the processing of the data for resp. FRHBO, FRBOU and FRHBO+FRBOU. For FRHBO (4 turbines) the total CPU time is 42.09 s and the maximum RAM consumption is 2599.86 MB. For FRBOU (6 turbines) the total CPU time is 67.49 s and RAM consumption is 4325.06 MB resp.. And for the FRHBO+FRBOU (10 turbines) the total CPU time is 110.29 s and RAM consumption is 6841.83 MB resp.. This indicates that the Dashboard_Preparation subapp can easily be run on standard server equipment. Scalability is also not an issue.

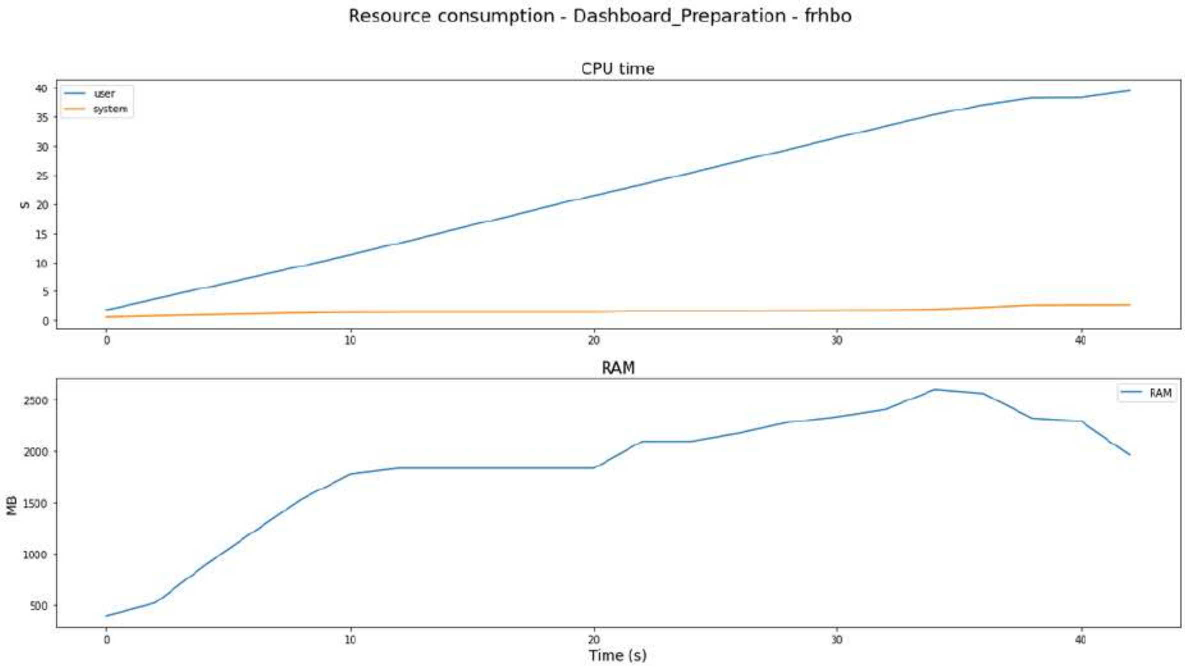


Figure 28: Resource consumption by Dashboard_Preparation for processing FRHBO.

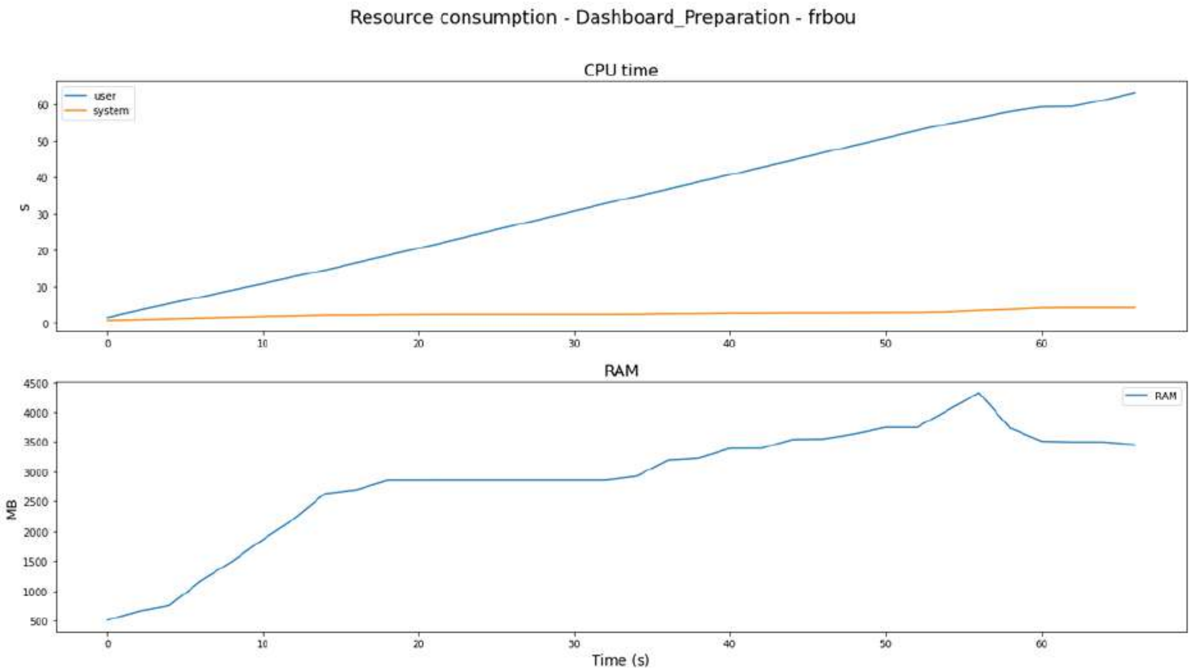


Figure 29: Resource consumption by Dashboard_Preparation for processing FRBOU.

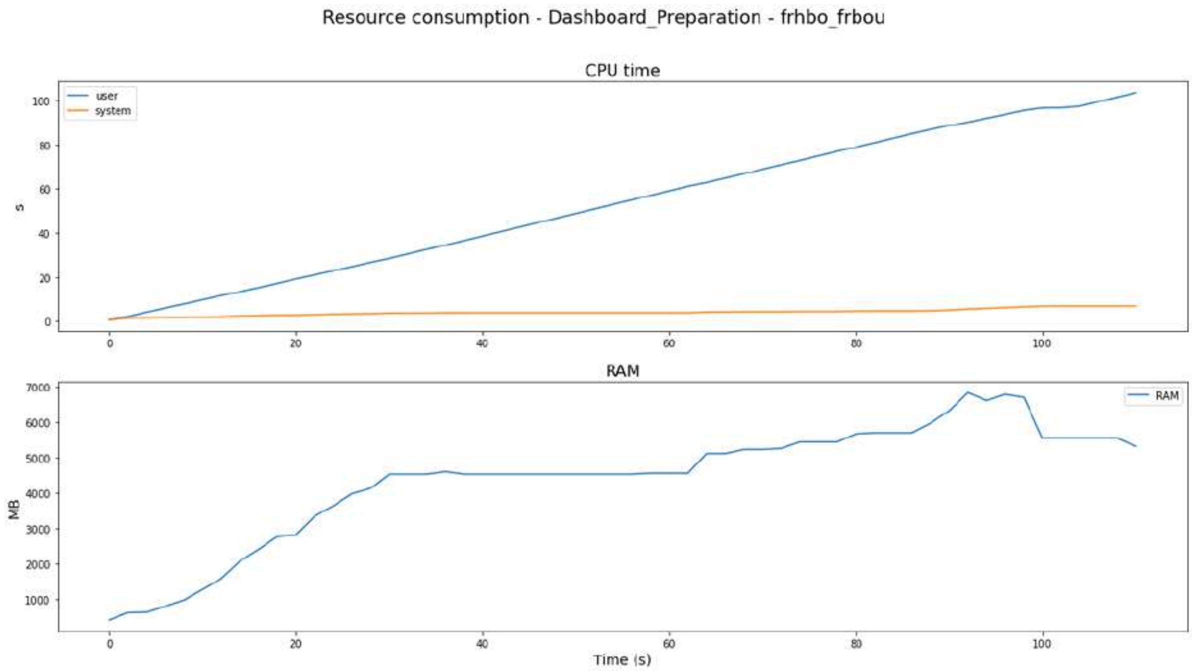


Figure 30: Resource consumption by Dashboard_Preparation for processing FRHBO+FRBOU.

The CPU time for executing the whole pipeline is:

- FRHBO: 18838.49 s.
- FRBOU: 40914.43 s.
- FRHBO+FRBOU: 94957.05 s.

The execution time on VM with 20 cores:

- FRHBO: 1102.38 s.
- FRBOU: 2281.72 s.
- FRHBO+FRBOU: 5118.92 s.

The maximum RAM consumption:

- FRHBO: 3972.05 MB.
- FRBOU: 5290.18 MB.
- FRHBO+FRBOU: 7440.78 MB.

Conclusion:

Running the data analytics pipeline on standard server equipment is feasible given the size of the ENGIE Senvion wind farms. Processing data from larger farms is also feasible. The part of the pipeline that scales the least is the Anomaly_Detection application. However, processing data from very large farms (>50 turbines) is still feasible on a standard server. If required, extra cores can be assigned to the Anomaly_Detection application, so that even lager farms can be processed in an acceptable time span. The RAM consumption does not seem to be a problem. For farm sizes comparable to those in the ENGIE Senvion dataset, this is not at all an issue.

KPI 5

KPI description:

The reduction in the maintenance cost of the wind turbine due to early fault detection. Less consequent damages are present and maintenance actions are clustered. Costs will be estimated by comparing cost of component replacement at detection to catastrophic failure. Revenues during additional time that the machine was able to run are subtracted from the maintenance costs.

To assess whether this KPI has been achieved, the most expensive failure case, the generator bearing failure, is discussed.

Assumptions:

- Rated power turbine = 2.05 MW.
- A generator bearing failure happens once every 10 years.
- Based on the performance of the data analytics toolbox, 3 out of 4 generator bearing failures can be detected.
- A generator bearing failure results in a downtime of 14 days, preventive maintenance of a damaged generator bearing results in a downtime of 1 day.
- The repair time when the generator bearing has failed is 3 days. If the bearing is replaced as part of a preventive maintenance than the repair time is 1 day.
- The price of labour = 1000 € / day.
- The price of electricity = 50 € / MWh.
- The capacity factor of the turbines = 0.2.
- The components that need to be replaced cost 15000 €.

Results: The expected costs due to generator bearing failures is without using the data analytics pipeline 2488.8 € / year for a turbine. If the data analytics pipeline is used the costs decrease to 1859.10 € / year. This corresponds to a cost reduction of 25.30%.

Conclusion:

The target value for KPI 5 was determined as 10-20% reduction in maintenance costs. The threshold value was set at 10%. The results show that the KPI is achieved.

KPI 6

KPI description:

The increase of the turbine availability due to faster actions triggered by better predictive maintenance. We focus on machines with an error.

Abs(Availability as is situation – Availability after usage of Platoon toolbox)

To validate whether this KPI has been achieved, we again use the generator bearing failure case.

Assumptions:

- A bearing failure happens once every 8 years.
- Based on the results of the data analytics toolbox, 3 out of 4 generator bearing failures can be detected.
- If a bearing fails it takes 3 weeks to repair the damage, if a bearing is replaced before failure it takes 1 day to repair.

Results:

- Increase of turbine availability for turbine CV5: 2.72%.
- Increase of turbine availability for turbine PH5: 2.42%.
- Increase of turbine availability for turbine HBO2: 3.34%.
- Increase of turbine availability for turbine HB3: 2.49%.

Conclusion:

The target value for KPI 6 was determined as 2-5% increase in availability. The threshold value was set at 2%. The results show that the KPI is achieved.

2.3 Conclusion

As a conclusion of the first validation, it can be drawn that the hybrid digital twin has reached the target KPIs regarding the modelling quality, integration, fault detection and processing capabilities. Furthermore, the results suggest a significant reduction of maintenance costs while the availability remains almost constant. Nevertheless, the results are not fully conclusive due to the assumptions made and would need to be further validated with the corresponding business units. . The KPIs related to the VUB data analytics pipeline have all been achieved .

3. Pilot 2A Evaluation & Validation Report

3.1 Introduction

Electricity balancing is a set of actions and processes performed by a TSO to ensure that total electricity withdrawals (including losses) equal total injections in a control area at any given moment. Electricity production from solar and wind plants is subject to considerable forecast errors that drive the demand for accurate forecasting of production of electricity. At each point in time, total production, combined with interchange, i.e., export or import of energy from/to control area, must be equal to total consumption (LLUC-03) in order to stabilize system frequency and to maintain exchange at scheduled levels; it is therefore also called load-frequency control. If the system runs out of balance, power stability and quality will deteriorate, which may trigger the disconnection of system components, and ultimately, power blackouts.

In PLATOON Pilot #2a framework services were developed, integrated and deployed within the Institute Mihajlo Pupin (IMP) proprietary VIEW4 Supervisory control and data acquisition (system). The VIEW4 SCADA is deployed at many parts in the energy value chain in Serbia and the Region, however in PLATOON two plants are in the focus

- The Wind Plant Krnovo in Montenegro (LLUC-04)
- The PV Plant in Belgrade, Serbia (LLUC-05, LLUC-07)
- The VIEW4 SCADA deployed at the Joint Stock Company EMS (LLUC-03)

With the new Law[1] that was introduced in 2021, independent producers (IPP) and producers from distributed and renewable sources (DER) are actors in the balance reserve market. The increasing number of renewable energy resources such as photovoltaic (LLUC-05, LLUC-07) and wind power plant (LLUC-04) has a significant impact on the stability and power quality of electricity transmission. Therefore, one of the goals of Pilot 2a is to develop and test PLATOON services for more accurate prediction of renewable energy generation as well as more accurate load forecast. Finally, in pilot 2a we are interested in monitoring and analysing the output from the RES power plant for an asset management scenario (LLUC-07).

- [1] Law on Amendments to The Law on Energy ("Official Gazette of RS", No. 40/2021)

3.2 LLUC-2A-03-Load Forecasting

LLUC-3 was intended to provide load forecasting tool on the national level, so that precise energy dispatch and planning be carried out. This is crucial in order to maintain the grid stability. The focus was put on medium-term forecast, precisely day-ahead forecast with and hourly resolution, which is appropriate when forecast is intended to be utilized by energy dispatch optimization engine. Forecasting model was to designed to calculate output taking into consideration the previous 24-hour long hourly consumption and different time related parameters. Service itself is integrated with the PLATOON platform.

3.2.1 Evaluation and Validation

Within 2a LLUC-03, day-ahead hourly load forecaster on national level have been developed. It was designed as innovative hybrid model, a combination of kNN and convolutional neural networks (CNN). The model obtains load from the previous day and current time-related parameters, and provides forecasted Serbian national load.
During the training phase, highly precise national load was obtained directly from Serbian TSO. Similar data could be found on ENTSO-E Transparency platform. Nevertheless, data that is being sent to the platform is not equally precise. Therefore, in order to validate the model with the same data that was used during training process, so that performance of the model is not jeopardized, similar data is gathered in batches by IMP. Hence, validation is carried out continuously, but on the delayed data.
Completely the same procedure with continuous validation could be applied to ENTSO-E or any other data source in the future.
Since forecasted and real national load are time series by their natures, common performance measurements have been selected as the most representative for the validation purposes. As given in Annex of this document, the list of the relevant KPIs for this service is following:

- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error (MPAE)
- Root Mean Square Error (RMSE)
- Root Mean Square Error Percentage (RNSEP)

Example of the forecasting model output is given in Figure 24 left, whilst in the right hand of the figure the errors through forecasting samples are given. It could be noticed that maximal absolute error is a bit more than 200kW which is quite small, taking into consideration that total load is approximately between 2400kW and 4500kW. Additionally, the current values of the KPIs are given in the table below. Similarly, to what was concluded in deliverable D4.4 Analytical Toolbox for Smart Grids, the model is quite precise and it could be utilized for load balancing on the national level.

Table 14: LLUC-2A-03- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1a	Mean Absolute Error (MAE) [MW]	260	145	Updated values have been calculated on the validation data, and hence are representative for the purpose of load forecasting model performance. For all four predefined KPIs, actual value is lower than the target one, resulting with the conclusion that the proposed solution fulfilled the requirements.
1b	Mean Absolute Percentage Error (MPAE)	10	3	
2a	Root Mean Square Error (RMSE) [MW]	260	195	
2b	Root Mean Square Error Percentage (RNSEP)	10	4	

There, KPI evaluation on the complete validation period is given. Similarly, to what was concluded in deliverable D4.4 Analytical Toolbox for Smart Grids, the model is precise and it could be utilized for the load balancing on the national level. Model has achieved desired performances since for all four KPIs calculated performance is better than the target value. Moreover, validation service for daily KPI calculation has been developed and is continuously calculating forecasting performance. An example of the visualization of the corresponding results is given through visualization tool for validation purposes, presented in Figure 31.

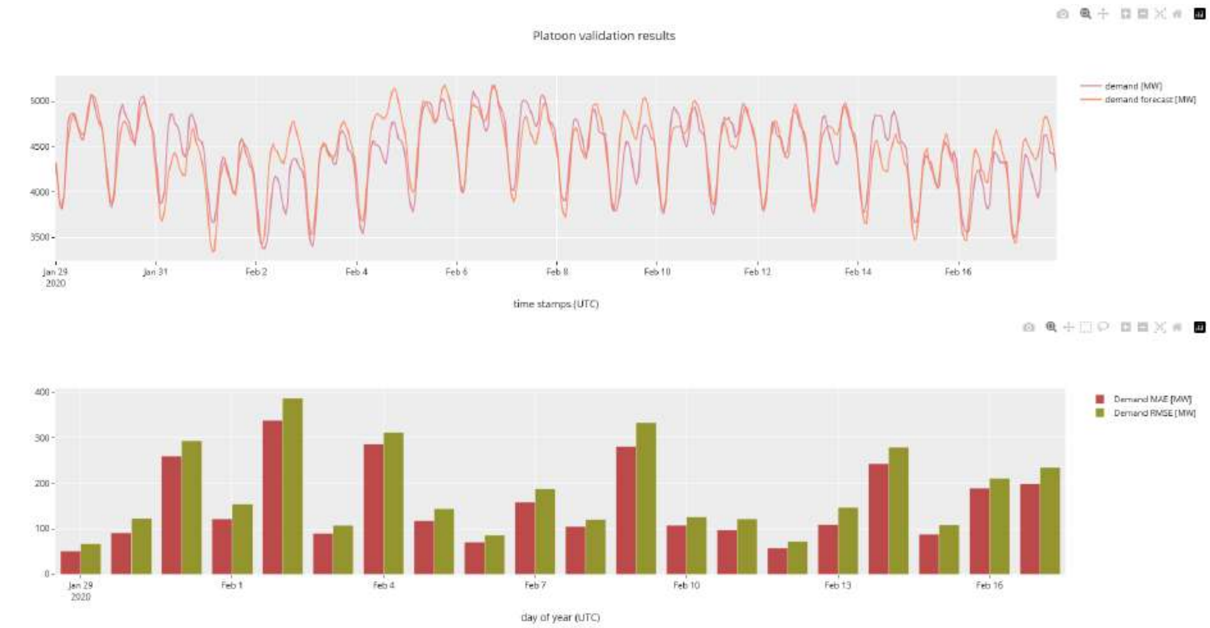


Figure 31 - Visualization of validation results through validation visusualization tool

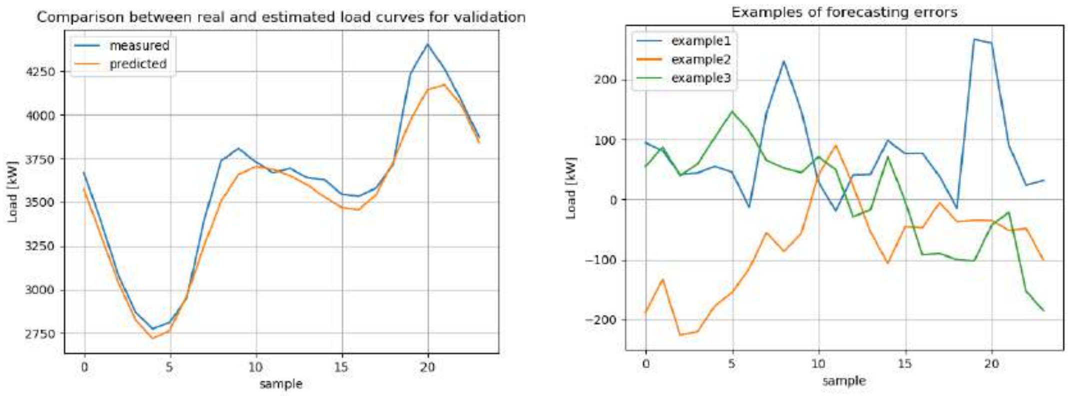


Figure 32 - Comparison between real and estimated load curves (left) and examples of forecasting errors (right)

3.3 LLUC-2A-04-RES Production Forecasting

Motivation for the development of RES production forecaster is similar as for the load one. Namely, with the goal of reducing the use of fossil fuels, renewable energy sources (RES), such as photovoltaic panels and wind turbines were introduced in the last decade. However, due to their high correlation with the stochastic meteorological conditions, it is not easy to match demand and production which is essential for maintaining the stable grid.

Hence, within LLUC-04 wind turbine production forecast was developed. Estimation was calculated based on the forecasted meteorological conditions by WeatherBit web service. Similarly, to use case 2A LLUC-03, day-ahead forecasting with hourly resolution was considered. The service was integrated with the rest of the platform through the data base i.e., all necessary inputs are obtained from the data base, and outputs are stored within the data base as.

3.3.1 *Evaluation and Validation*

As explained in deliverable D4.4 Analytical Toolbox for Smart Grids, a production forecaster based on LSTM neural networks has been developed, integrated and deployed. The example of different outputs of the production forecaster extracted from PLATOON MySQL is given in Figure 33. During the operation time, it was noticed that forecasting for some time was invalid, due to the fact that historical wind speed measurements corresponded to different height than the once from the WeatherBit service. Nevertheless, estimation of the wind speed at the considered height was evaluated as:

$$speed = speed_0/k * \ln{(h/h_0)}$$

and service was updated accordingly.

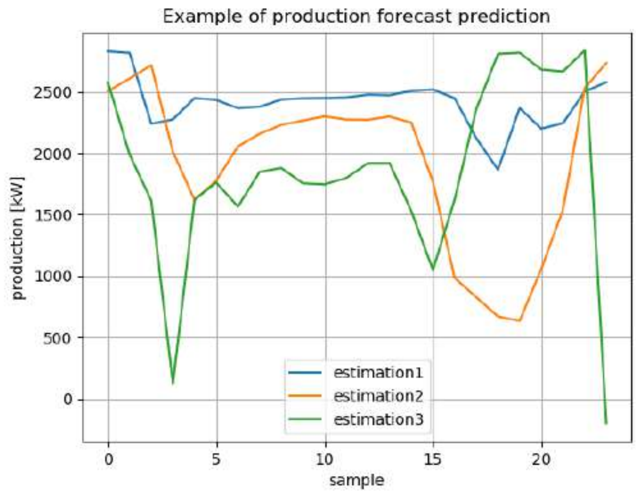


Figure 33 - LLUC-2A-04-Example of production forecast estimations

Since, forecasted and real production are time series by their natures, common performance measurements have been selected as the most representative for the validation purposes. As given in Annex of this document, the list of the relevant KPIs for this service is following:

- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error (MPAE)
- Root Mean Square Error (RMSE)
- Root Mean Square Error Percentage (RNSEP)

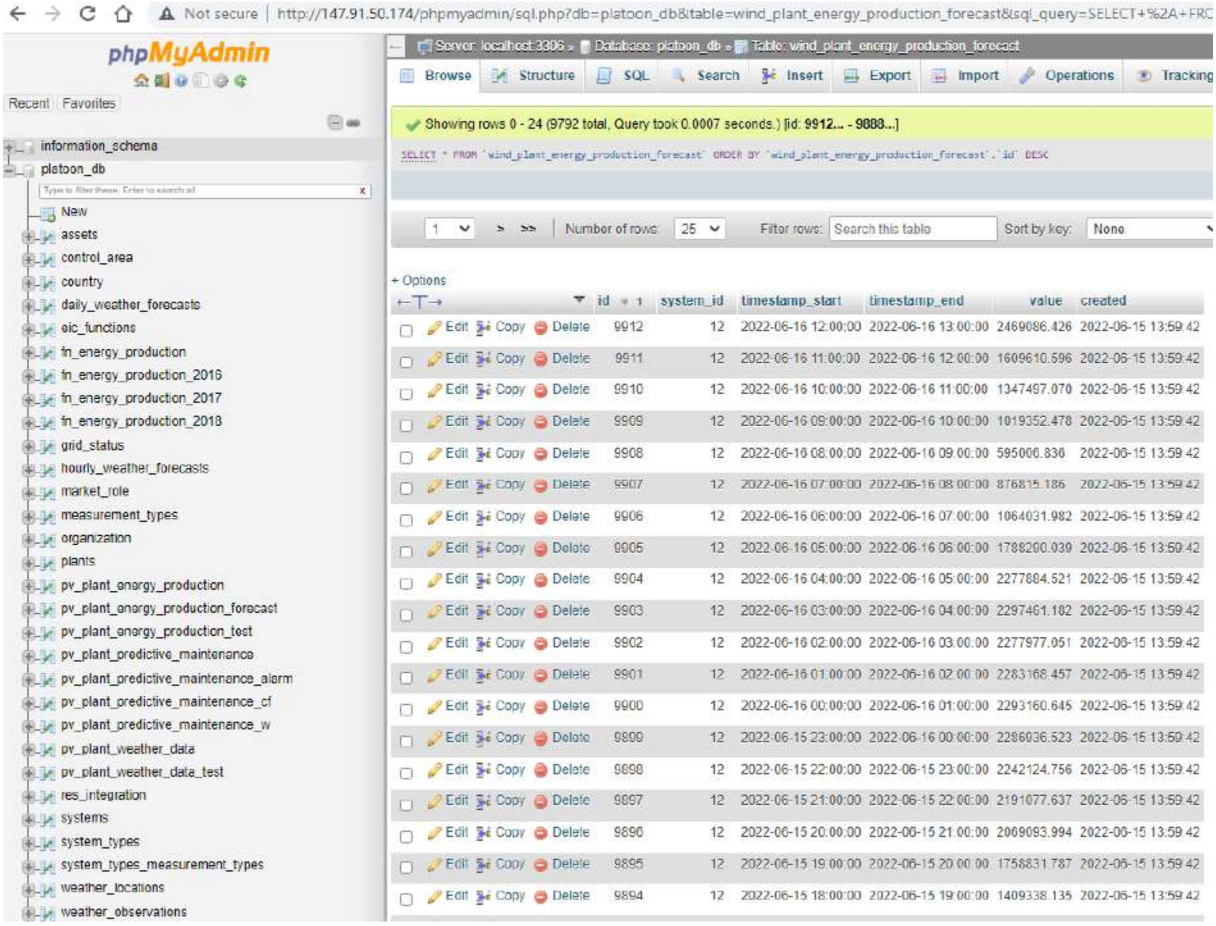
Similar to the previous load forecasting service, production data is obtained in batches from Krnovo SCADA. Current KPIs could be seen in the table below and it could be observed that all KPIs are satisfactory. Namely, the model precision is relatively high, especially having in mind that the main input, wind speed, a highly fluctuating quantity, is only considered on an hourly basis.

Table 15: LLUC-2A-04- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1a	Mean Absolute Error (MAE) [MW]	260	139	Due to the change in SCADA system, it was impossible to obtain additional amount of data for validation, and hence, no update could be provided for production forecaster.
1b	Mean Absolute Percentage Error (MPAE)	10	8	
2a	Root Mean Square Error (RMSE) [MW]	260	159	

2b	Root Mean Square Error Percentage (RNSEP)	10	10	Nevertheless, it is expected, in accordance with the performance that has already been analysed within WP4 and previous WP6 deliverables, that models are in achieving target performances.

As it could be noticed from Figure 34, the service is successfully working and storing outputs in PLATOON MySQL DB.



id	system_id	timestamp_start	timestamp_end	value	created
9912	12	2022-06-16 12:00:00	2022-06-16 13:00:00	2469086.426	2022-06-15 13:59:42
9911	12	2022-06-16 11:00:00	2022-06-16 12:00:00	1609610.596	2022-06-15 13:59:42
9910	12	2022-06-16 10:00:00	2022-06-16 11:00:00	1347497.070	2022-06-15 13:59:42
9909	12	2022-06-16 09:00:00	2022-06-16 10:00:00	1019352.478	2022-06-15 13:59:42
9908	12	2022-06-16 08:00:00	2022-06-16 09:00:00	595006.836	2022-06-15 13:59:42
9907	12	2022-06-16 07:00:00	2022-06-16 08:00:00	876815.186	2022-06-15 13:59:42
9906	12	2022-06-16 06:00:00	2022-06-16 07:00:00	1064031.982	2022-06-15 13:59:42
9905	12	2022-06-16 05:00:00	2022-06-16 06:00:00	1788290.039	2022-06-15 13:59:42
9904	12	2022-06-16 04:00:00	2022-06-16 05:00:00	2277884.521	2022-06-15 13:59:42
9903	12	2022-06-16 03:00:00	2022-06-16 04:00:00	2297461.182	2022-06-15 13:59:42
9902	12	2022-06-16 02:00:00	2022-06-16 03:00:00	2277977.051	2022-06-15 13:59:42
9901	12	2022-06-16 01:00:00	2022-06-16 02:00:00	2283168.457	2022-06-15 13:59:42
9900	12	2022-06-16 00:00:00	2022-06-16 01:00:00	2293160.645	2022-06-15 13:59:42
9899	12	2022-06-15 23:00:00	2022-06-16 00:00:00	2286036.523	2022-06-15 13:59:42
9898	12	2022-06-15 22:00:00	2022-06-15 23:00:00	2242124.756	2022-06-15 13:59:42
9897	12	2022-06-15 21:00:00	2022-06-15 22:00:00	2191077.637	2022-06-15 13:59:42
9896	12	2022-06-15 20:00:00	2022-06-15 21:00:00	2069093.994	2022-06-15 13:59:42
9895	12	2022-06-15 19:00:00	2022-06-15 20:00:00	1758831.787	2022-06-15 13:59:42
9894	12	2022-06-15 18:00:00	2022-06-15 19:00:00	1409338.135	2022-06-15 13:59:42

Figure 34 - LUC-2A-04- Illustration of production service filling in MySQL table

3.4 LLUC-2A-05-RES effect calculation

The objective of this use case is to analyse unexpected variations (voltage profile of the power system) before and after RES integration to the power system. Since the services need real-time data with high reporting rates of the grid status, a PMU is deployed at the Edge. In addition, analytics tools are also deployed at the edge.

3.4.1 Evaluation and Validation

Table 16: LLUC-2A-05- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1	Increase in PV insertion capacity	> 100 %	150 %	KPI is calculated daily, therefore the minimal value is only reported in this table.

The KPI was calculated in a few steps utilizing the data from the PMU and actual production of the installed PV (P_n = 50 kWp). The service first measures the grid with PV and estimates the state of the grid without the PV. The main goal is to estimate the impedance of the line towards the substation from the measurements. According to the calculated impedance and maximally allowed voltage on the LV grid defined by standard EN-50160, the maximum PV power can be estimated (see Figure 35). Then, for each day, the insertion capacity is calculated. However, in the case of bad weather, the results are not reported due to higher uncertainty, hence some missing values can be seen. Finally, the insertion capacity is normalized to the installed PV plant, which is 50 kWp resulting in a KPI higher than 150 %, with an average value of more than 200 % (see Figure 36).

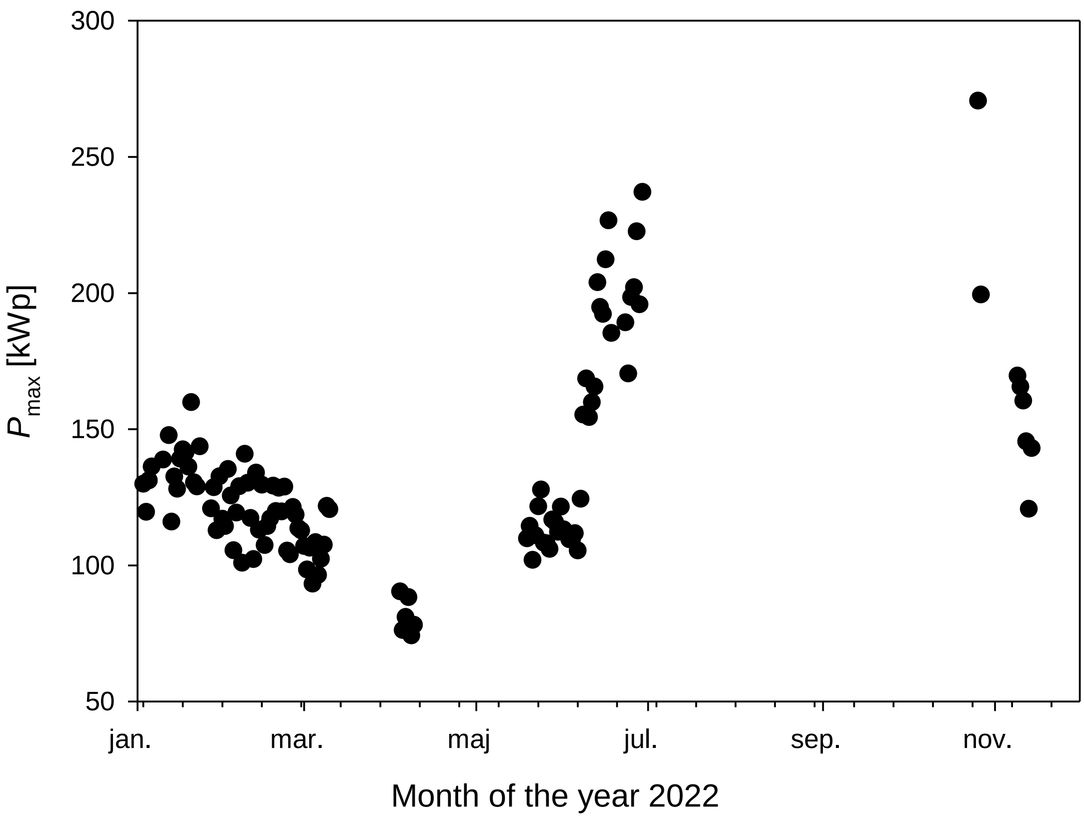


Figure 35: LLUC-2A-05- Maximal PV insertion capacity for the LV Grid.

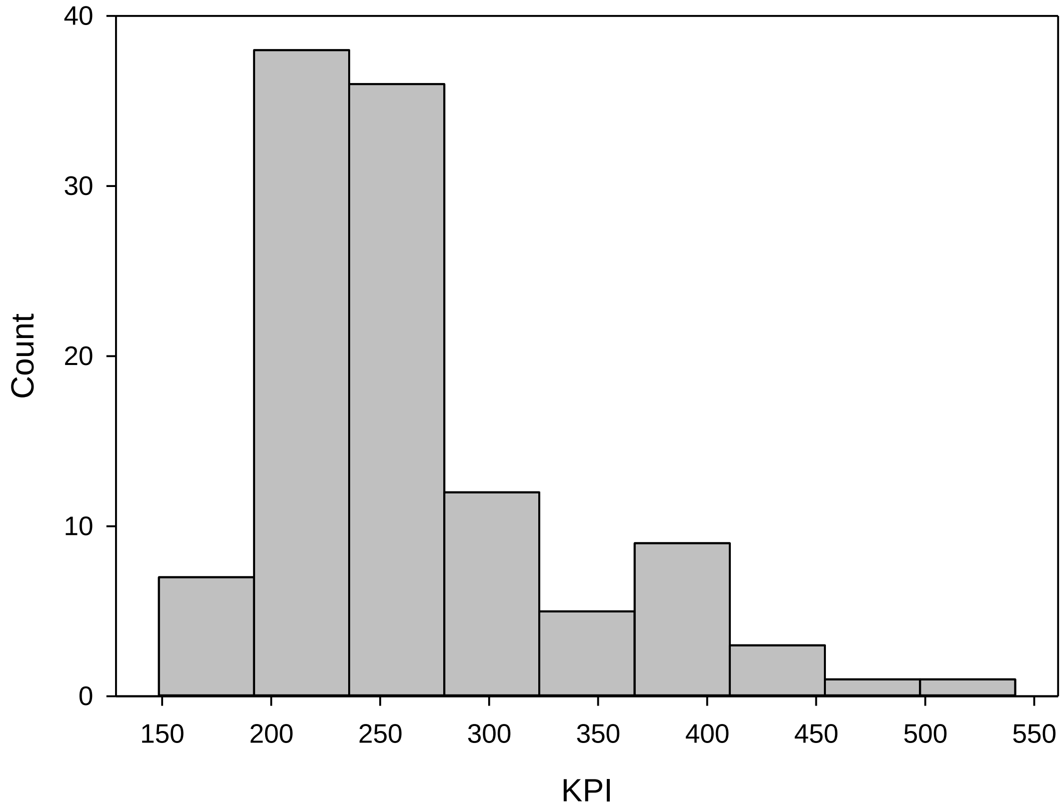


Figure 36: LLUC-2A-05- Histogram of calculated KPIs for the current year.

The service runs locally on the edge computer next to the existing PV plant using the edge-cloud framework as described in deliverable D4.2. The service is dockerized and executed once a day. The results are saved in the IMP SQL database on the central computer. In the future, we will monitor the execution of the service and analyze the reported results. This will be further evaluated to remove the results with higher uncertainty to get an even better insertion capacity estimation.

3.5 LLUC-2A-07-PV Predictive maintenance

The objective of this use case is to develop a set of data analytics tools that use existing data from sensors and whether to predict and monitor the degradation of the modules of PV plants.

3.5.1 Evaluation and Validation

Table 17: LLUC-2A-07- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1	Saving costs	> 0 €	10.62 € (estimation)	Calculated by injecting an error and estimating 3 days to notice a malfunctioning of inverter by periodic manual inspection.

According to the KPI template, all the steps to calculate the KPIs are already done. However, since the modules are still in good condition with an estimated degradation of around 1% (see Figure 37), the calculation has not yet triggered an alarm. Due to seasonal fluctuations in the performance of the PV plant, more data is needed to estimate the PV modules degradation more accurately.

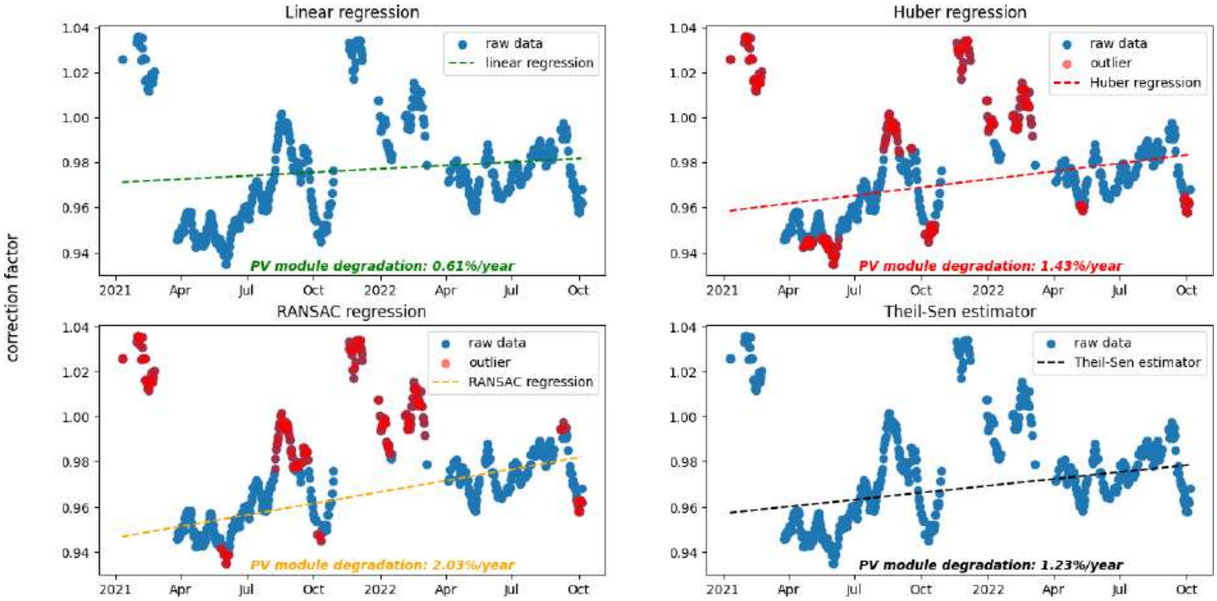


Figure 37: LLUC-2A-07- Daily calculated c.f. for the PV plant installed at IMP and estimated PV module degradation using different linear regression algorithms.

The calculation is done for two types of failures: on the one hand, the estimation of the failure of inverters that are constantly monitored and for which the alarm is triggered when an anomaly is detected, and on the other hand, the performance of the modules which is evaluated once per day. During the deployment period, none of the alarms was triggered, so the KPI for cost savings was not calculated. Therefore, we injected the error into the grid, by modifying the coil turn ratio on phase 2 on the PMU by factor 10. This means the live data was distorted and the service has successfully detected an error in phase 2, Figure 38.

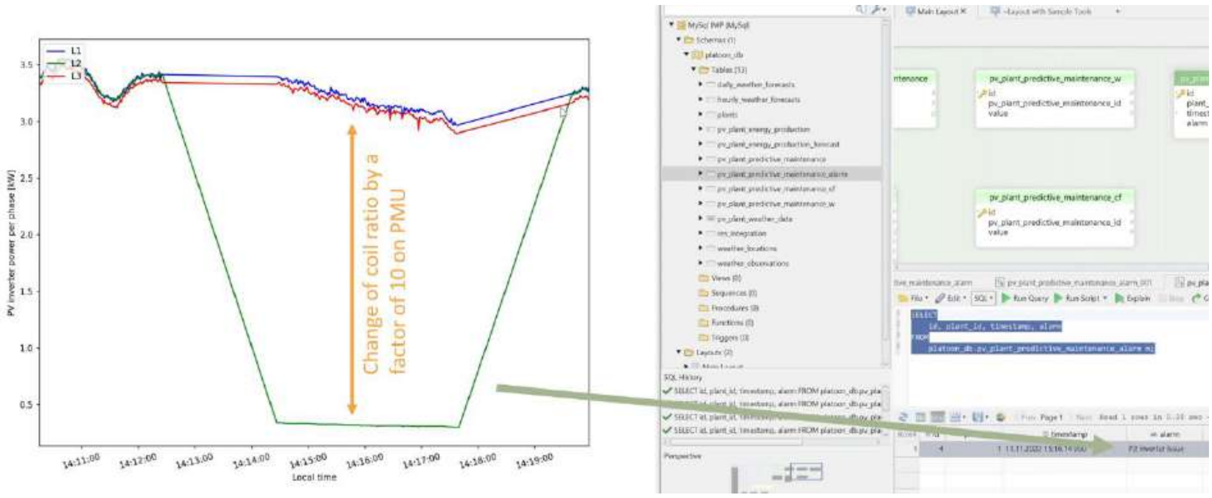


Figure 38: LLUC-2A-07- On the graph, live values of PV inject power as reported by PMU before, during and after changing the coil ratio and real-time query of an alarm from the database.

For final evaluation of KPI, we have assumed the following parameters:

- $N_{days\_estimate}$ = 3, the typical value if the manual inspection is performed periodically.
- E_{daily} = 60 kWh (one inverter, month November)
- Price = 0.059 €/kWh[i]

From these parameters, the final KPI was evaluated:

KPI = 3*60 kWh*0.059kWh = 10.62 €

The grid is monitored every 5 minutes, so the estimate of the number of days after the estimate of failure $N_{days\_after\ detectingfailure}$ = 0 is valid. The service is dockerized and deployed to the edge computer next to the PV system. The service checks the voltages and the symmetry of the inverter-related powers for all three phases (see Figure 39), and can immediately report an alarm about the failure into IMP MySQL.

```
if np.nanmean(P) > 3000:
    if np.nanmean(V1) < 180:
        write_alarm(now, "V1 issue")
    if np.nanmean(V2) < 180:
        write_alarm(now, "V2 issue")
    if np.nanmean(V3) < 180:
        write_alarm(now, "V3 issue")
    if np.nanmean(P1) < np.nanmean(P) / 5:
        write_alarm(now, "P1 inverter issue")
    if np.nanmean(P2) < np.nanmean(P) / 5:
        write_alarm(now, "P2 inverter issue")
    if np.nanmean(P3) < np.nanmean(P) / 5:
        write_alarm(now, "P3 inverter issue")
```

Figure 39: LLUC-2A-07- Part of code that constantly monitors the inverters and reports alarms to IMP MySQL.

3.6 Conclusions

Pilot 2a consists of four LLUC and most of those were validated even during the first validation period. However, for LLUC 7, which is related to predictive maintenance, it was not possible to estimate the corresponding KPI(s), since no maintenance was required due to good condition of the assets. Therefore, no problems were registered during the final stage of validation, error on the grid side was artificially injected and the service was validated, resulting with the satisfactory results. Additionally, within the previous version of this report, LLUC 3 and 4 were validated on the old data. Therefore, additional data was obtained for LLUC 3 and KPIs for different time intervals have been calculated. These KPIs showed even better performance of the service then estimated before, proving that target was achieved. Unfortunately, an additional amount of data for LLUC 4 was inaccessible, so no updates are present. Finally, it could be concluded that the final validation corroborated previous conclusions that all services are achieving desired performances.

4. Pilot 2B Evaluation & Validation Report

4.1 Introduction

This pilot consists in two Use Cases related with the electricity grid stability, connectivity and life extension of the components in a smart grid in ParcBit, Majorca (Spain). The ese cases defined within this pilot are the following:

- LLUC-2B-01 Predictive Maintenance for MV/LV Transformers.
- LLUC-2B-02 Detection of NTL in electrical grids.

4.2 LLUC-2B-01 Predictive Maintenance for MV/LV Transformers

This use case focuses on transformer predictive maintenance, estimating transformer components health and its maintenance costs, planning maintenance actions, monitoring transformer alarms and studying different grid scenarios in case of replacing old transformers or adding complementary transformers.

4.2.1 Evaluation and Validation

As stated in the D6.8, some of the KPIs defined had been replaced due to analyzed power transformers have not experienced any failures since their installation date, and the algorithms developed do not expect them to fail during the next years. So all the supervised metrics, in the confusion matrix (TP,TN,FP,FN) and the metrics derived from it as Cohen Kappa cannot be calculated. Because of this, Health models have been validated by the combination of model correlation parameters and testing the RUL and overload models against the Common Network Asset Indices Methodology [2].

Table 18: LLUC-2B-01- KPIs evaluation

KPI #	Description	Target Value	Actual Value (SAM)	Actual Value (TECN)	Actual Value (IND)	Comments
1	Temperature estimation accuracy (%)	5%	1.05%	0.30%		A validation of different virtual sensor algorithms with different features has been done and the one with the best results has been reported (see results below).

[2] Ofgem. (2017). DNO Common Network Asset Indices Methodology.

14	Useful Life Extension (years)	Equal results as standards			Results equal to target.	Comparison with standard calculations IEC60076-7 and CNAIM.
15	Predictive Mean Error	<5% of variable value			All variables <1%	Each model variable must be evaluated.
16	Predictive Mean Absolute Error	<5% of variable value			All variables <1%	Each model variable must be evaluated.
17	Predictive Mean Percentage Error	<5% of variable value			All variables <1%	Each model variable must be evaluated.
18	Predictive Mean Percentage Absolute Error	<5% of variable value			All variables <1%	Each model variable must be evaluated.
19	Predictive Mean Squared Error	<5% of variable value			All variables <1%	Each model variable must be evaluated.
20	Predictive Root Mean Squared Error	<5% of variable value			All variables <1%	Each model variable must be evaluated.
21	Correlation Coefficient R2	0.85 or higher			All variables >0.9	Each model variable must be evaluated.

Regarding the temperature estimation accuracy (%) of the top oil temperature virtual sensor, different algorithms with different features have been validated and a benchmarking analysis has been performed. The models of top oil temperature have been developed using distinct sensor configurations, going from low amount of necessary installed sensors to a configuration where all sensors need to be installed. This comparison allows future installations to decide the amount of investment on sensors depending on the required accuracy.
Table 19 shows the results of the models developed by SAM. The accuracy for each model is registered with %MAE and the test data comprises the 25% of the data that has been selected randomly.

Table 19: LLUC-2B-01- Sampol - Top Oli Temperature model results

Model	Train set MAE	Test set MAE
LV_load+Room_temp	2.07%	2.16%
LV_load+nearest_public_temp	3.55%	3.65%
LV_load+Room_temp+1Case_Sensor	1.30%	1.32%
Room_temp+1Case_Sensor	2.12%	2.42%
LV_load+Room_temp+1Case_Sensor+MV_load	3.55%	3.54%
LV_load+Room_temp +MV_load	2.12%	2.42%

The expected results are that the error decreases when using more sensors. However, the problem of the models that include MV load data is that the sensors have been installed and configured later than the rest. This implies that these models are trained with less data and obtains worse results than the rest.

Without installing the MV sensors, the best results are obtained when one of the case temperature sensors is installed. But in fact, the cost of this sensors must be considered due to the low difference of accuracy between models.

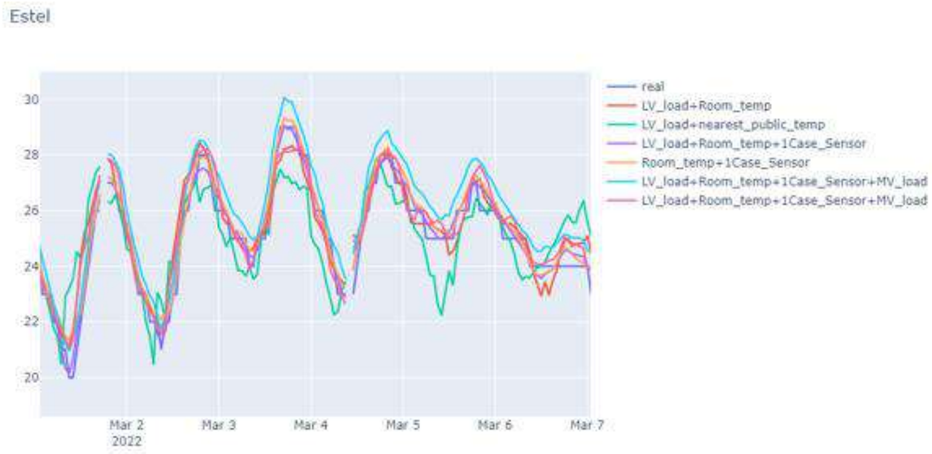


Figure 40: 2b-01 KPI 1 - Comparison of the temperature estimation between all trained models

On the one hand, regarding the models developed by Tecnalia the one that provided the best results provided a MAPE of 0.23%. The figure below shows the validation results of the best performing top oil temperature virtual sensor model over a period of 2 months (15/01/22 – 15/03/22). As it can be seen the predicted value (orange) is very close to the real value (blue). Also, it can be seen that there is a gap from 17/01/22 to 14/02/22 where there is no validation data. This was due to a problem with the integration of the current analyser in the primary winding of the transformer. For the final version of the deliverable (V2) the model will be validated with more recent data to confirm if the results are still comparable.

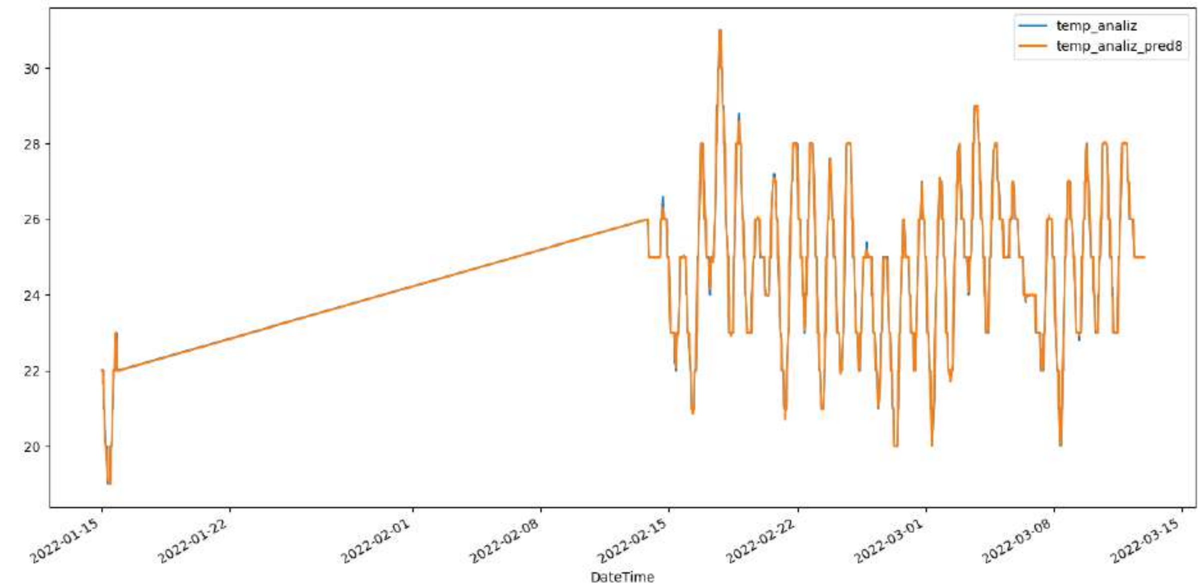


Figure 41 LLUC-2B-01- Top oil temperature virtual sensor best performing model validation results

Besides, regarding the predictive monitoring tools for electrical transformers, several functionalities regarding the and health-related issues that have been implemented so far. However, no real-time processing and validation has been done yet, so the application of the previously defined KPIs has not been possible until now. This document summarizes the evaluation and validation actions hitherto accomplished.

There is a fast model, (executing every 10 mins) and a slow model (executing every hour); the second one includes the last three signals from the table above. The models are trained using historical data (the training sample). Ideally, the dataset used as the training sample should cover the range of variation of those signals representing boundary conditions (i.e., ambient temperature or transformer power load).
As a result of the training, the tool displays a series of statistical indicators showing the accuracy of the estimation model in the case of every variable. These indicators include:

- ME (Mean Error)
- MAE (Mean Absolute Error)
- MPE (Mean Percentage Error)
- MAPE (Mean Percentage Absolute Error)
- MSE (Mean Squared Error)
- RMSE (Root Mean Squared Error)
- R2 (Correlation coefficient)

The following figure shows a sample of the results obtained for the previous accuracy indicators for some of the signals under analysis.

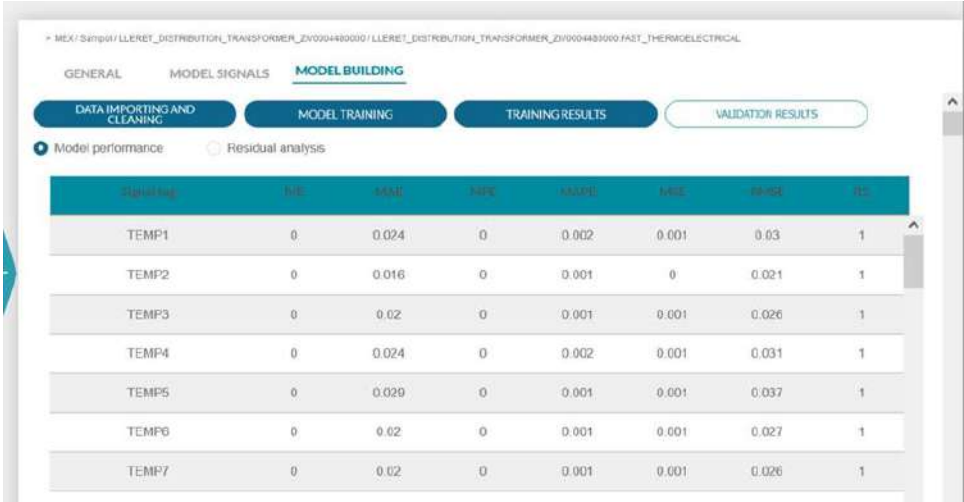


Figure 3 LLUC-2B-01- Training results for the predictive model training

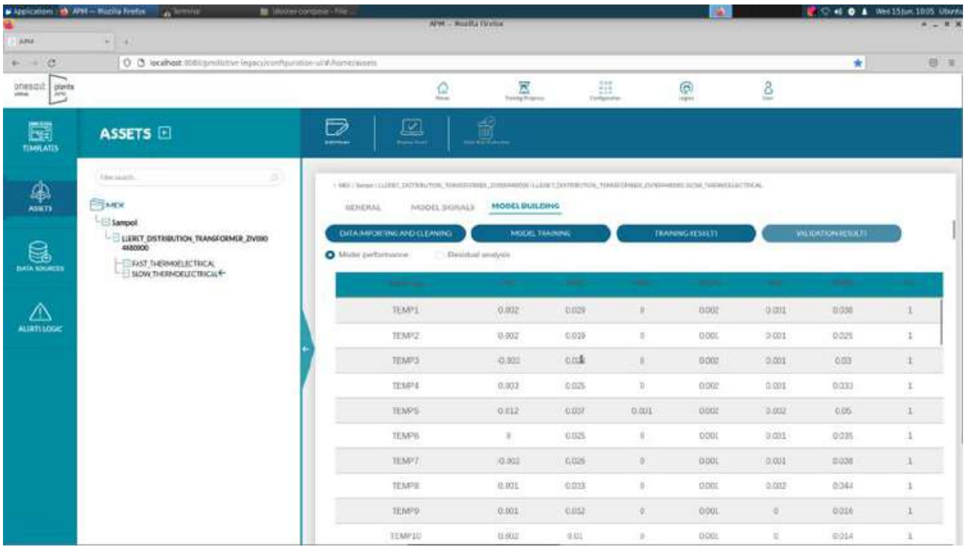


Figure 4: LLUC-2B-01- Validation results for the predictive model training

The results obtained in the training of the predictive model are quite good, thus anticipating a suitable fit in the future operation with real-time data. In addition, 30% of training selected points are randomly excluded from model training and used in an automatic validation. Results are similar to those in model training.

As far as the health-index related modules are concerned (replacement and overload calculations) the situation is similar since no real-time operation has been implemented yet. The modules have been designed and programmed and currently have undergone unitary tests, covering:

- Data model and conversion to different data formats (serialization and deserialization to protocol buffers or json)
- Data base interactions (get, insert, delete and update)
- General service (protocol buffer queries and serialization)
- Calculation functions

These tests have been run with actual data and compared with manual calculations according to each standard (CNAIM and IEC60076-7). Manual calculations have been previously validated with examples contained on standard definitions. For results testing purposes, calculations of each standard have been separated in several functions:

- **IEC60076-7:**
    - Theta0
    - ThetaHs
    - DeltaH1
    - DeltaH2
    - Aging factor
    - Actual Relative S to nominal apparent Power
    - Overaging
    - Whole combined calculation
- **CNAIM:**
    - Location factor
    - Duty factor
    - Observed condition
    - Oil Condition
    - Dissolved Gases Condition
    - Furfurladehyde oil condition
    - Initial Health score
    - Estimated health score along time
    - Financial consequences factor
    - Financial estimation of time to change
    - Whole combined calculation

The accuracy of calculation software tests is over 99%.
In the case of the models developed by TECNALIA, the final top oil temperature model has been developed with a random forest regressor which input features have been:

- ✓ The active energy at the secondary winding of the transformer
- ✓ The 8 temperatures at the outside of the transformer casing
- ✓ The temperature, humidity and pressure inside the transformer cabinet
- ✓ The temperature, humidity and pressure outside the transformer cabinet

All these features have been used in hourly periods, downsampling the available values where needed.

On average, and taking into account the total number of registers available for each transformer, 619 for W, 2815 for Lleret and 3466 Estel) the average error of the model is 0.30%, much lower than the error obtained applying the IEC 60076-7 standard to predict TOT temperature, which is the 7.20%.

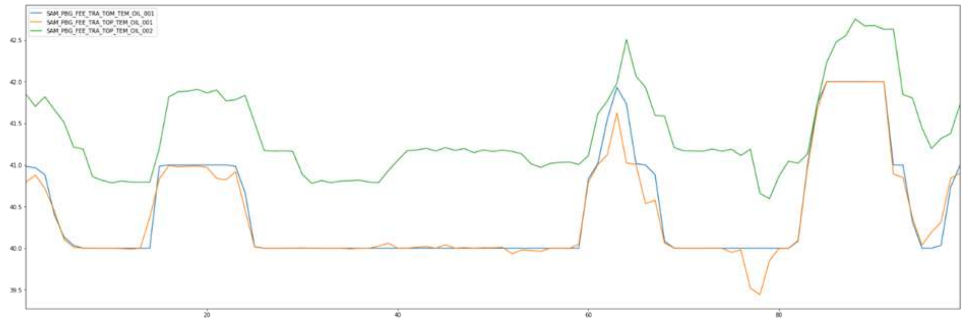


Figure 21. TOT real sensor (blue line), TOT virtual sensor (orange line) and TOT IEC model (green line) values for the W transformer

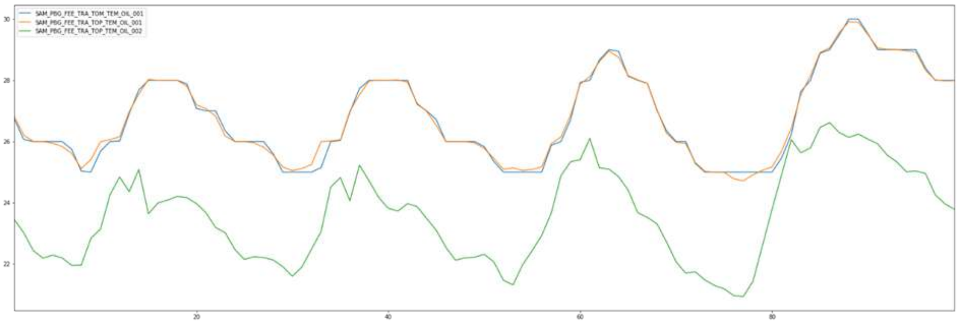


Figure 22. TOT real sensor (blue line), TOT virtual sensor (orange line) and TOT IEC model (green line) values for the Lleret transformer

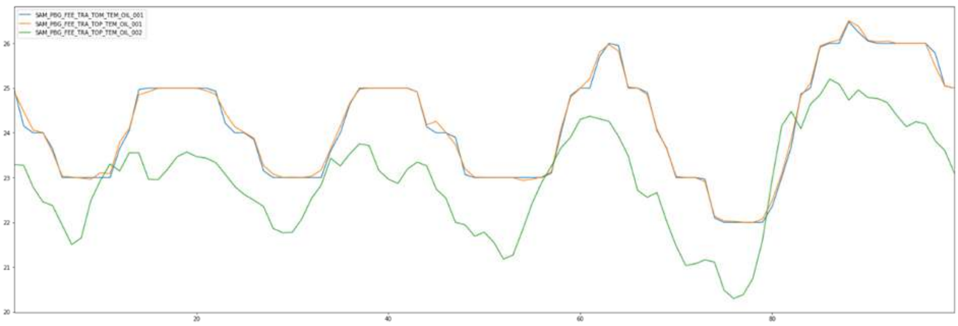


Figure 23. TOT real sensor (blue line), TOT virtual sensor (orange line) and TOT IEC model (green line) values for the Estel transformer

For the HST calculation, TECNALIA has applied a model based on the exponential equations of the IEC 60076-7 standard. This model has been fed with the hourly measurements of the previous and current load factor (Q) and TOT temperature, and the model parameters have been set to the advised values provided by the IEC 60076-7 standard itself, for small size ONAN transformers.

The obtained results for the HST temperature shows that the HST temperatures are very low.

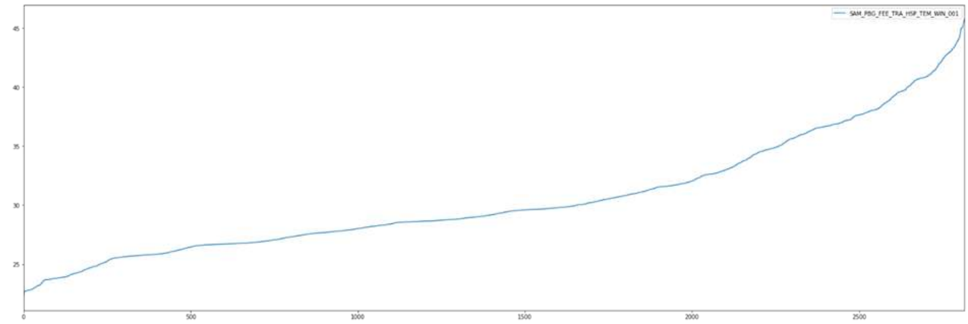


Figure 24. HST temperatures (°C) in ascending order for the Lleret transformer

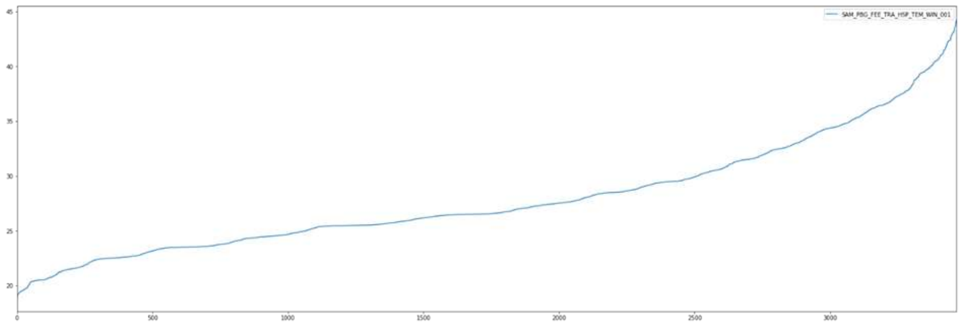


Figure 25. HST temperatures (°C) in ascending order for the Estel transformer

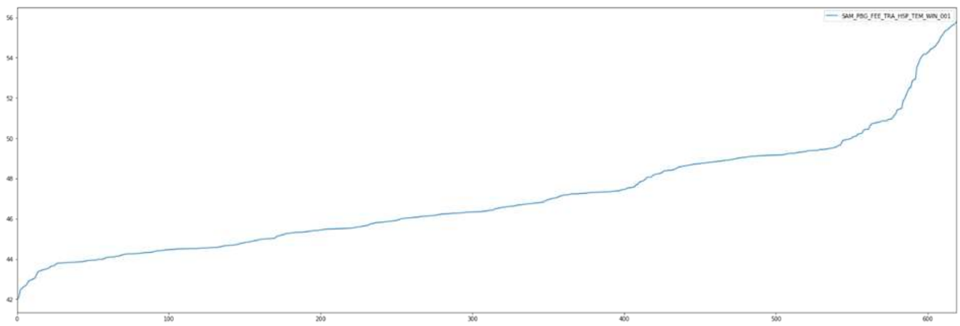


Figure 26. HST temperatures (°C) in ascending order for the W transformer

The reason for these low temperatures is the relatively low load factor to which the transformers are charged.

Table 15. Load and HST factor for each transformer.

Average (%)	Lleret	Estel	W
load_factor	6.55	7.67	29.58
HST_factor	36.79	31.64	46.11

These results show that As transformers are very underloaded, HST factor is far below its rated maximum value (65 °C over ambient temperature). This HST factor is the maximum temperature difference over ambient temperature that the manufacturer guarantees, when the transformer is operated at rated load factor (100%).

The following figures illustrate both the load factor and the HST factor in boxplots, to show the correlation between low load factors and low HST factors.

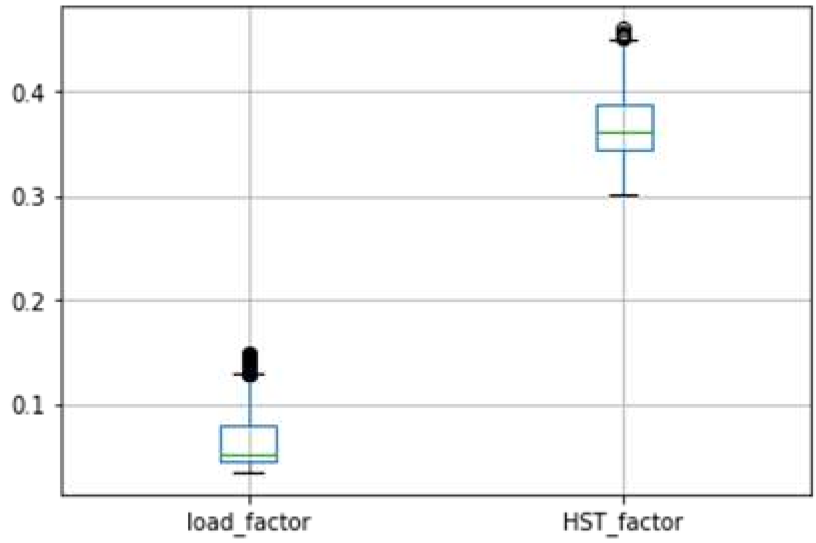


Figure 27. Load and HST factors for the Lleret transformer

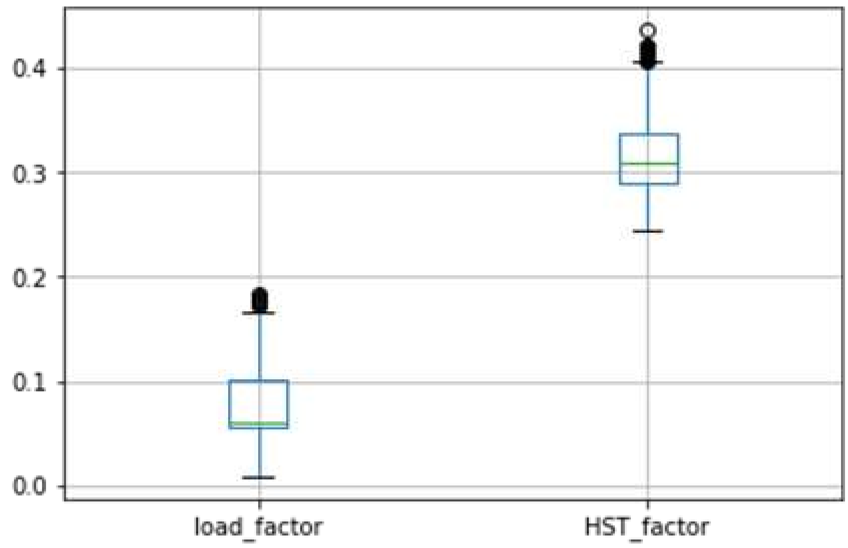


Figure 28. Load and HST factors for the Estel transformer

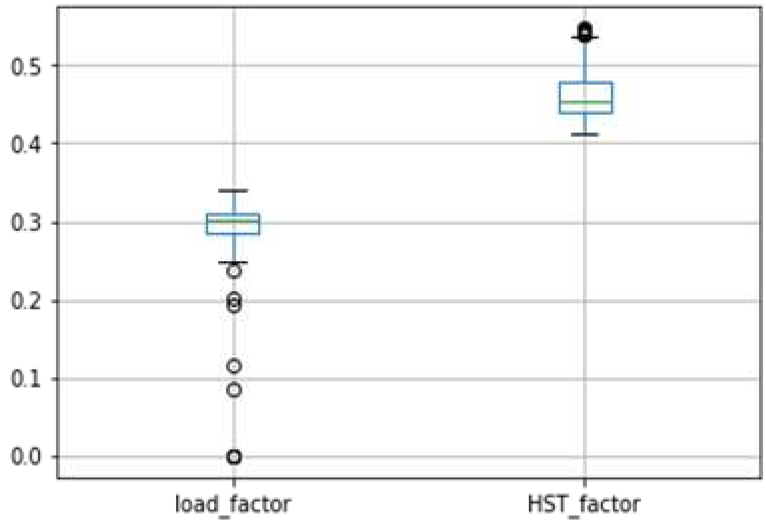


Figure 29. Load and HST factors for the W transformer

Finally, with the HST temperatures the loss of life of each transformer was calculated.

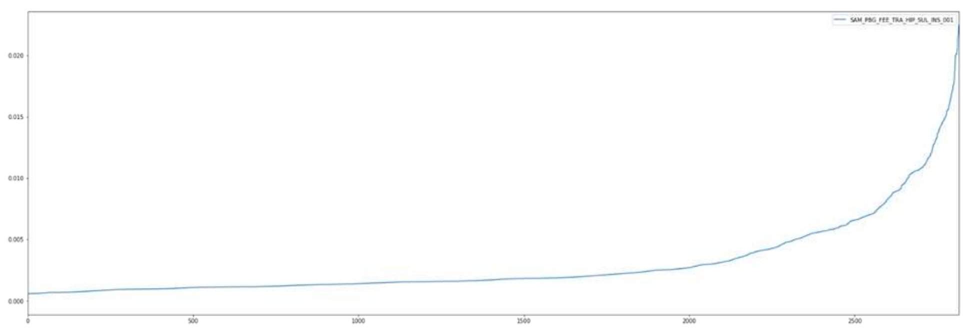


Figure 30. Loss of life (min) in ascending order for the Lleret transformer

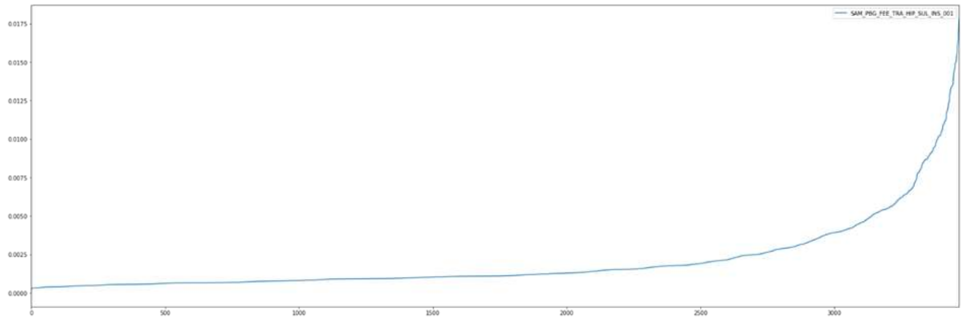


Figure 31. Loss of life (min) for the Estel transformer

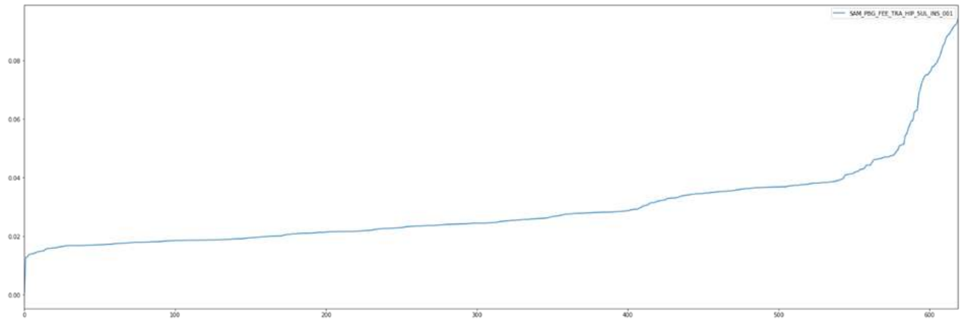


Figure 32. Loss of life (min) for the W transformer

On average, for all the hourly periods for which we have had data for each transformer, the loss of life for each hourly period has been almost insignificant. Even in the case of W, which the transformer with the highest average load factor, the degradation of the insulation health during the test period has been so low that we can conclude that it has not been degraded.

Loss of life (seg)	Lleret	Estel	W
Hourly average	0.18	0.12	1.76

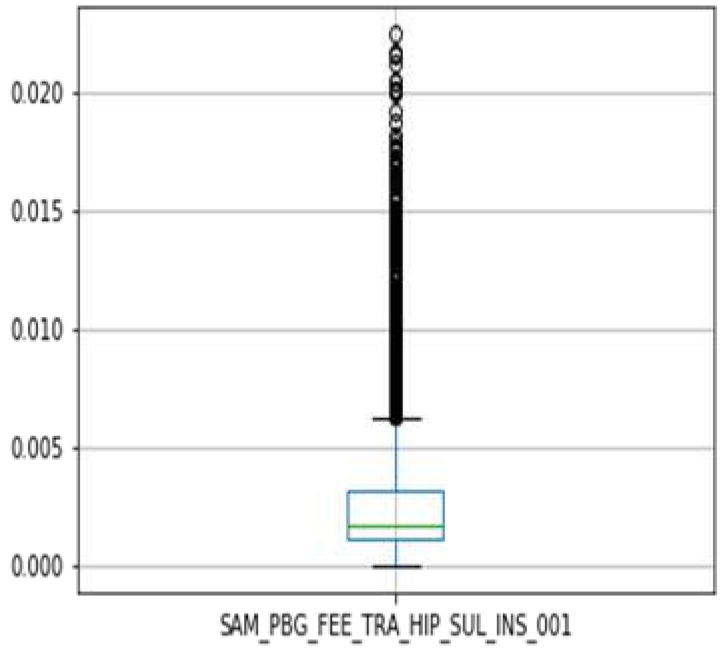


Figure 33. Boxplot of loss of life (min) for the Lleret transformer

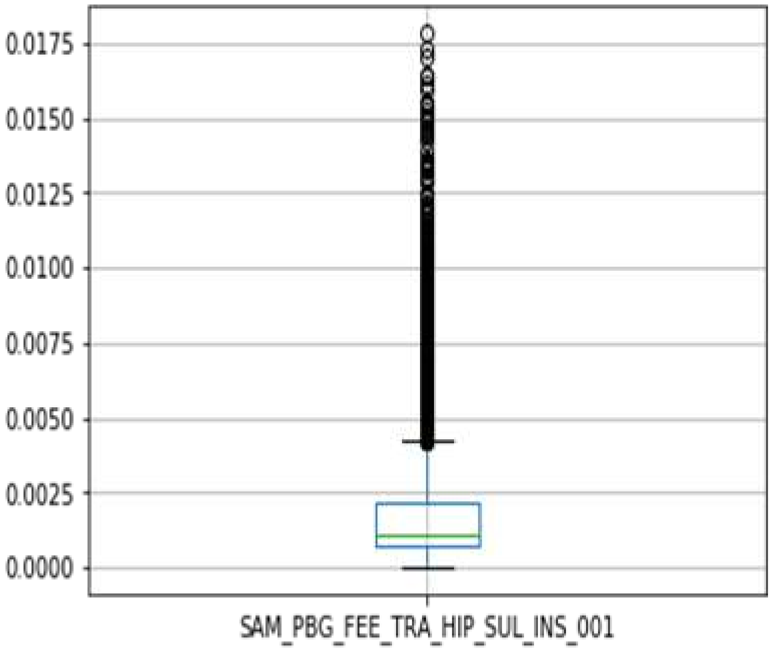


Figure 34. Boxplot of loss of life (min) for the Estel transformer

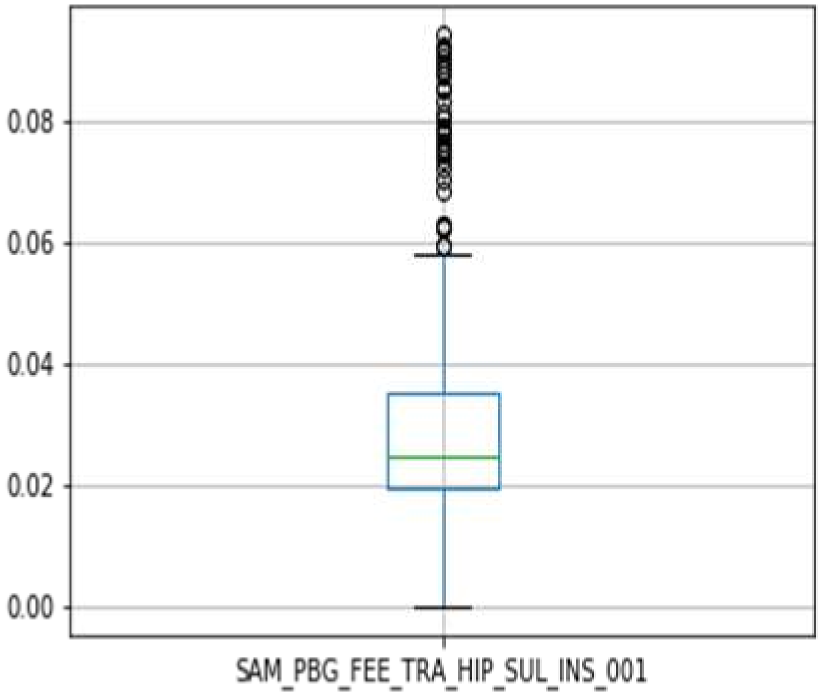


Figure 35. Boxplot of loss of life (min) for the W transformer

4.3 LLUC-2B-02 Detection of NTL in electrical grids

The main objective of this use case is to develop a tool for the quantification of losses in the distribution grid of a DSO and the detection of non-technical losses (NTL), using the available smart meter data.

4.3.1 Evaluation and Validation

In the previous version of this deliverable, and due to the validation method adopted of introducing synthetic anomalies into the dataset, the originally defined target values became outdated. As synthetic data is introduced for validation purpose, the target values should be adjusted because the final dataset with synthetic data implies that results of all KPI will be artificially modified.

The modification is simple, as the synthetic data is known (Created with the methodology explained below), the effects of it over the KPI can be calculated. For example, in the global losses energy percentage (KPI-01), the target value has to be increased with all the energy consumption that is added with the synthetic data. For the confusion matrix, the expected true positives are known, as they are the number of anomalies introduced, the same for the TN.

All the target values have been modified to be significative after the addition of the synthetic data, considering the original values.

Table 20: LLUC-2B-02- KPIs evaluation

KPI #	Description	Target Value	Previous Values	Actual Value,	Actual Value,	Actual Value,	Actual Value,	Comments

			(Sampol last delivered Model)	**Sampols update model fine tuned**	**Sampols New RC Model**	**Tecnalia models**	**Indra models**	
1	Global Losses Energy Percentage	<30%	25.61%	25.61%	25.61%	25.61%	15.76%[3]	Calculated with the synthetic data, average between all loops. This value is calculated using all the available data, target and actual values are bigger than the expected because prosumers data sometimes is not sent by the prosumer smart meters. IND results filter some meters in one of the concentrator (Estel).
2	NTL Energy Percentage	<15%	11.26%	11.26%	11.26%	11.26%	1.43%	Calculated with the synthetic data, average between all loops. Addition of Customer and Non-Customer NTL percentage. IND results filter some meters in one of the concentrator (Estel).
3	TL Energy Percentage	<25%	14.35%	14.35%	14.35%	14.35%	14.35%	Calculated with the original data. This value is calculated using all the available data, target and actual values are bigger than the expected because prosumers data sometimes is not sent by the

								prosumer smart meters.
4	Customer NTL Energy Percentage	<10%	1.43%	1.43%	1.43%	1.43%	1.43%	Calculated with the synthetic data, average between all loops.
5	Non-customer NTL Energy Percentage	<10%	9.83%	9.83%	9.83%	9.83%	0%	Calculated with the synthetic data, average between all loops. Indra models' do not detect non-NTL fraud, so the cannabinol synthetic data was removed.
6	True positives (TP)	>7.45 %	1.64%	4.03%	8.10%	6.56%	3.47%	Number of anomalies detected correctly. There are 99 anomalous patterns added with the synthetic dataset, this implies that the 9,06% of the values is anomalous.
7	False Positives (FP)	<8.96 %	18.39%	1.19%	11.39%	36.81%	9.82%	Anomalies detected not generated at synthetic data.
8	False Negatives (FN)	<2.29 %	3.01%	4.57%	4.08%	2.49%	5.58%	Anomalies not detected by the algorithms.
9	True Negatives (TN)	>81.3 %	76.48%	89.75%	76.45%	54.13%	81.11%	Normal behaviour data with no anomalies detected. There are 994 non anomalous patterns at the synthetic dataset.
10	Specificity (%)	>70%	80.62%	98,69%	87.03%	46.3%	89.2%	The algorithm does detects 90% of the anomalies.
11	Sensitivity (%)	>52%	35.29%	46.81%	66.66%	86.6%	38.4%	The algorithm classifies 80% non-anomalous smart meters correctly.

12	Cohen's Kappa (%)	>50%	6.2%	55.37%	42.60%	27%	22.79%	It is a low value of kappa. But can still be valid until there is no stablished limit.
13	Economic Savings (€)	-	215€	529 €	1063 €		380,82€	Calculated as the average detection of synthetic anomalies multiplied by the average KWh price between iterations of validation. IND Calculated as the average of losses multiplied by the average KWh price for business.

As there are no real anomalies classified in the past, to validate this use case, a synthetic anomaly generator has been developed. It is based on the work done at [ii] to generate two types of anomalies: shunt and interrupted shunt, and to model cannabinol farms with energy demand curves dependent on plants cultivating periods, as this is one of the most common tapping NTL patterns[4].

The synthetic data has been generated in a loop until 94 anomalies are generated (this number is calculated using Cochran technique [iii] to assure that the results are statistically significant). This strategy avoids the introduction of too much simultaneous anomalies. It is not expected that a big number of prosumers starts developing fraud during the same period. Each loop follows the next steps:

1. The percentage of anomalous smart meters is selected to be between [5%,10%] of the total number of smart meters registered.
2. Generate between 0 and 2 cannabinol farms started in a date randomly selected from the range [2022-01-01, 2022-06-01] and of farm size randomly chosen between 5 and 10 square meters, also a random moment of production at connection time.
3. Each anomaly starts in a date randomly selected from the range [2022-01-01, 2022-06-01].
4. The anomaly type is selected randomly between shunt and Interrupt shunt.
5. The effect of the shunt is randomly selected from the range [25%,85%].
6. The anomalies created using the interrupt shunt technique, are generated with an interrupt coefficient selected randomly from the range [50%,90%].
7. Detect the anomalies using the synthetic data.

[4] Mehboob, N., Farag, H. E., & Sawas, A. M. (2020). Energy consumption model for indoor cannabis cultivation facility. IEEE Open Access Journal of Power and Energy, 7, 222-233

8. Clear anomalous noise and go back to step 1.

The improvement of energy losses evaluates the reduction of technical energy losses in the distribution network. The Platoon project is not addressing the actions that can be implemented in order to minimize them, but the objectives are aimed at the implementation of new or improvements in existing algorithms for their detection and identification with the evident purpose of designing subsequent actions for their reduction (outside the project scope).

Another objective is to deploy these algorithms at the node level so that the detection of these possible losses is carried out at the local level, thus minimizing the volume of data that must be sent to the central systems for its calculation, the capacity of processes in these central systems therefore the necessary calculation times.
During the second validation phase, Sampol included a new method based on Reservoir computing and fine-tuned the previous model. The results obtained by the fine-tuned version of the first tool passed all the KPI thresholds, and just 3 of them were below the objective, nearly reaching it.
In parallel to the fine tuning, the Reservoir computing version was developed. Reservoir Computing is a type of neural network with a special way of training process. This are initiated randomly and the only training is done to the last layer of the network as it was a linear regression, so the computational cost is the cost of inverting a matrix. This implies that it can be trained at edge.

Validation of new developments of the NTL identification model:

Validation of the Shunt fraud events detection:

Tables 15 and 16 present the performance metrics (TP, FN, FP, TN, Specificity [0, 1], Sensitivity [0, 1]) per use case and iteration (fraud file) for the Shunt fraud events detection. For W, 4 different fraud files for Shunt are created, 23 for Lleret and 17 for Estel. Note that the detection is referred to daily fraud events.

Table 16. Performance metrics per use case after the removal of False Positives (step 1) for Shunt detection.

	W	LLERET	ESTEL
True Positives	[7, 7, 3, 7]	[0, 1, 1, 0, 0, 0, 2, 1, 3, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0]	[38, 74, 69, 87, 64, 66, 74, 29, 73, 26, 13, 89, 86, 6, 0, 94, 55]
False Negatives	[117, 102, 36, 100]	[96, 105, 69, 62, 90, 16, 136, 103, 138, 139, 78, 106, 39, 52, 60, 25, 89, 132, 22, 18, 2, 123, 42]	[0, 53, 5, 45, 19, 27, 5, 0, 37, 0, 0, 46, 39, 0, 114, 50, 0]
False Positives	[0, 0, 0, 0]	[0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0]	[0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0]

True Negatives	[27, 42, 108, 44]	[53, 42, 79, 86, 59, 132, 12, 45, 9, 11, 70, 41, 108, 96, 88, 122, 60, 18, 126, 129, 146, 25, 106]	[48, 8, 43, 2, 39, 31, 42, 48, 22, 47, 47, 3, 10, 48, 18, 1, 48]
Specificity	[1.0, 1.0, 1.0, 1.0]	[1.0, 0.97, 1.0, 1.0, 1.0, 1.0, 0.92, 1.0, 0.9, 1.0, 1.0, 0.97, 0.99, 1.0, 1.0, 0.99, 1.0, 1.0, 1.0, 0.99, 1.0, 1.0, 1.0]	[1.0, 1.0, 0.98, 0.66, 1.0, 1.0, 0.98, 1.0, 1.0, 0.98, 0.98, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0]
Sensitivity	[0.05, 0.06, 0.07, 0.06]	[0.0, 0.0, 0.01, 0.0, 0.0, 0.0, 0.01, 0.0, 0.02, 0.0, 0.01, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]	[1.0, 0.58, 0.93, 0.66, 0.77, 0.71, 0.93, 1.0, 0.66, 1.0, 1.0, 0.65, 0.68, 1.0, 0.0, 0.65, 1.0]

As can be observed in Table 15, the specificity is high in all use cases, i.e., there are few false positives, and the sensitivity is low in Lleret and W, which means that there are many false negatives. Nevertheless, it works well as an offline fraud detection tool in which the main objective is decide if fraud events are committed in a period.

Table 16 presents the performance metric results per use case without the step 1 of removal of FPs. As can be observed, the sensitivity metric has increased because more True Positives are detected, but the specificity decreases as more FPs arise.

Table 17. Performance metrics per use case without the removal of False Positives (step 1) for Shunt detection.

	W	**LLERET**	**ESTEL**
True Positives	[124, 108, 37, 107]	[44, 105, 25, 62, 31, 12, 94, 45, 84, 22, 68, 107, 39, 11, 0, 19, 0, 1, 8, 18, 0, 42, 0]	[38, 82, 73, 132, 64, 73, 78, 29, 84, 26, 13, 134, 119, 6, 0, 129, 55]
False Negatives	[0, 1, 2, 0]	[52, 1, 45, 0, 59, 4, 44, 59, 57, 118, 11, 0, 0, 41, 60, 6, 89, 132, 14, 0, 2, 82, 42]	[0, 45, 1, 0, 19, 20, 1, 0, 26, 0, 0, 1, 6, 0, 114, 15, 0]

False Positives	[15, 8, 12, 8]	[36, 14, 15, 18, 28, 18, 5, 6, 2, 0, 46, 14, 108, 19, 0, 43, 0, 0, 40, 47, 0, 8, 0]	[15, 3, 17, 3, 16, 10, 3, 21, 8, 19, 18, 0, 4, 13, 0, 0, 0]
True Negatives	[12, 34, 96, 36]	[17, 29, 64, 68, 31, 114, 8, 39, 8, 11, 24, 28, 1, 77, 88, 80, 60, 18, 86, 83, 146, 17, 106]	[33, 5, 27, 0, 23, 21, 40, 27, 14, 29, 30, 3, 6, 35, 18, 1, 48]
Specificity	[0.44, 0.81, 0.89, 0.82]	[0.32, 0.67, 0.81, 0.79, 0.52, 0.86, 0.61, 0.86, 0.8, 1.0, 0.34, 0.66, 0.0, 0.80, 1.0, 0.65, 1.0, 1.0, 0.68, 0.63, 1.0, 0.68, 1.0]	[0.68, 0.625, 0.61, 0.0, 0.59, 0.68, 0.9302325581395349, 0.56, 0.63, 0.60, 0.62, 1.0, 0.6, 0.73, 1.0, 1.0, 1.0]
Sensitivity	[1.0, 0.99, 0.95, 1.0]	[0.45, 0.99, 0.35, 1.0, 0.34, 0.75, 0.68, 0.43, 0.59, 0.15, 0.86, 1.0, 1.0, 0.21, 0.0, 0.76, 0.0, 0.0, 0.36, 1.0, 0.0, 0.34, 0.0]	[1.0, 0.65, 1.0, 0.77, 0.78, 0.98, 1.0, 0.76, 1.0, 1.0, 0.99, 0.952, 1.0, 0.0, 0.89, 1.0]

Validation of the Cannabinol fraud events detection:

As commented the procedure to detect the cannabinol fraud events is the same as in the Shunt fraud detection. In Table 17 the performance metric results obtained after the 1st (Detect false positive fraud events) and 2nd (Fraud detection) steps are shown. Table 18 presents the performance metric results without the removal of FPs (step 1). Note that the results are presented per case study and iteration and refer to daily fraud events. In this simulation, there are 6 files, i.e., iterations, for W, 3 for Lleret and 6 for Estel.

Table 18. Performance metrics per use case after the removal of False Positives (step 1) for Cannabinol detection.

	W	LLERET	ESTEL
True Positives	[4, 4, 4, 3, 7, 6]	[0, 0, 0]	[53, 66, 69, 64, 23, 43]

False Negatives	[50, 101, 88, 10, 108, 77]	[53, 15, 24]	[31, 46, 36, 41, 0, 0]
False Positives	[1, 1, 1, 1, 1, 1]	[1, 1, 1]	[1, 1, 1, 1, 1, 1]
True Negatives	[93, 42, 55, 133, 35, 66]	[94, 132, 123]	[25, 5, 16, 11, 47, 47]
Specificity	[0.99, 0.98, 0.98, 0.99, 0.97, 0.98]	[0.99, 0.99, 0.99]	[0.96, 0.83, 0.94, 0.91, 0.97, 0.97]
Sensitivity	[0.07, 0.04, 0.04, 0.23, 0.06, 0.07]	[0.0, 0.0, 0.0]	[0.63, 0.59, 0.65, 0.61, 1.0, 1.0]

Table 19. Performance metrics per use case without the removal of False Positives (step 1) for Cannabinol detection.

	W	**LLERET**	**ESTEL**
True Positives	[54, 105, 92, 13, 115, 83]	[53, 15, 24]	[64, 91, 86, 82, 23, 43]
False Negatives	[0, 0, 0, 0, 0, 0]	[0, 0, 0]	[20, 21, 19, 23, 0, 0]
False Positives	[94, 43, 56, 134, 36, 67]	[95, 133, 124]	[8, 3, 6, 4, 18, 18]
True Negatives	[0, 0, 0, 0, 0, 0]	[0, 0, 0]	[18, 3, 11, 8, 30, 30]
Specificity	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0]	[0.69, 0.5, 0.65, 0.66, 0.62, 0.62]
Sensitivity	[1.0, 1.0, 1.0, 1.0, 1.0, 1.0]	[1.0, 1.0, 1.0]	[0.76, 0.81, 0.82, 0.78, 1.0, 1.0]

As can be observed, the results follow the same trend as in Shunt fraud detection. The step 1 in which the FP are removed works well at the expense of detecting less TPs. The specificity is high but the sensitivity low. On the contrary, the sensitivity is high if the step 1 is not applied because more TPs are detected. However, the number of daily FPs are also higher. Note that the best achieved results are encountered for Estel.

4.4 Conclusion

Tests have been conducted both in the case of the predictive module training and unit tests for the health-related modules.
Regarding the validation of LLUC-2B-01 Predictive Mantainance of power transformers, the results of the top oil temperature virtual sensors are successful. The KPI related with the confusion matrix, and so on defined as supervised were unable to obtain. To validate the developed tools, a new set of KPI have been defined and passed successfully.
Regarding the validation of LLUC-2B-02 NTL detection use case, due to the lack of fraud data the developed models have been validated using synthetic data. The new models developed increased the True Positives and passed all the KPI thresholds, most of them getting over the target values. The Sampol fine-tuned first tool seems to be the more efficient as the false positives obtained are the lowest, and with the better results in specificity and Cohen's kappa, but the true positive KPI is lower than the one obtained by the Tecnalia and Sampol's new models, that also obtains higher False Positives. Depending on the availability of the DSO it may be more useful to first analyse the anomalies found by the Sampol's fine tunned first model and then use the other tools to analyse further NTL detected cases.

5. Pilot 3A Evaluation & Validation Report

5.1 Introduction

Pilot 3a is related to the ENGIE Lab CRIGEN building office located in the Paris region. The office has a Building Management System (BMS) controlling the HVAC and comfort in different zones of the building. Two low level use cases have been developed within the scope of this pilot:

- LLUC-3A-01-Optimizing HVAC control regarding occupancy.
- LLUC-3A-02-Provide demand response services through building inertia and HVAC controls.

5.2 LLUC-3A-01-Optimizing HVAC control regarding occupancy

This use case aims to provide an optimized operation schedule for each day of the week for the office building and its different zones based on the occupancy in the building and the comfort level required by the occupants. The HVAC optimization and control aims to:

- Optimize the building energy consumption.
- Maximize the comfort of occupants with the best energy efficiency.
- Automate HVAC system control and reduce manual intervention on system controls.

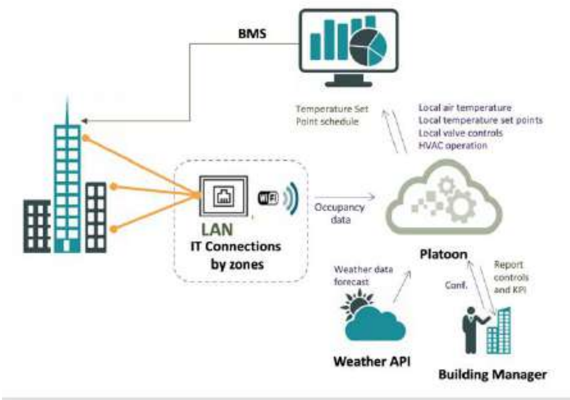


Figure 42: Pilot 3A LLUC01 schema

Different challenges were encountered in the implementation of the LLUC 01 and required updates and extra work on the use case:

- Quality of the input data and extra treatment required to assess the occupancy of the different zones in function of IT data connexion. Some extra data treatments were required, and a new service called "Tool 0" has been developed to get the actual occupancy status in the different rooms of the building in order to provide accurate occupancy status for the building occupancy forecaster.
- Heating and cooling of the building proved to operate not properly / exactly as expected. For heating and cooling, the local regulation was not often used in certain rooms (heating/cooling through ventilation and internal heat gain for example). Some of the controllers have schedule/setpoint problems that didn't really fit with a normal operation of the building. The data collected for the Data analytics model is then not so relevant.
- Challenges of managing heating and cooling (differences in the data), building operating both in heating and cooling at the same time with a regulation that is not optimal.

Sending orders to the BMS faced some protocols and technical difficulties that have been successfully resolved. After an important focus to tackle this subject in order to fully test the technologies developed within Pilot 3A use cases on the real system "the office building", it is now possible to send the Tool 2 pre-heating and pre-cooling schedules to the BMS and to control the temperature setpoints in the different zones of the building.

5.2.1 Evaluation and Validation

21An implementation has been conducted to collect and integrate the IT (from wifi and LAN) data required within the platform Pilot 3A , and to implement the pipelines and the AI services .

Some updates of the and the data pipeline have been performed to have the full environment with all the architectural components required to run efficiently the use case.

As explained in deliverable D4.5 Analytical Toolbox, three services have been developed withing this LLUC to create the building occupancy, to forecast the occupancy status in the different zones of the building and to project the occupancy status for pre-heating and pre-cooling purposes.

Below presented an example of the tools results

- **Building occupancy data status creation**

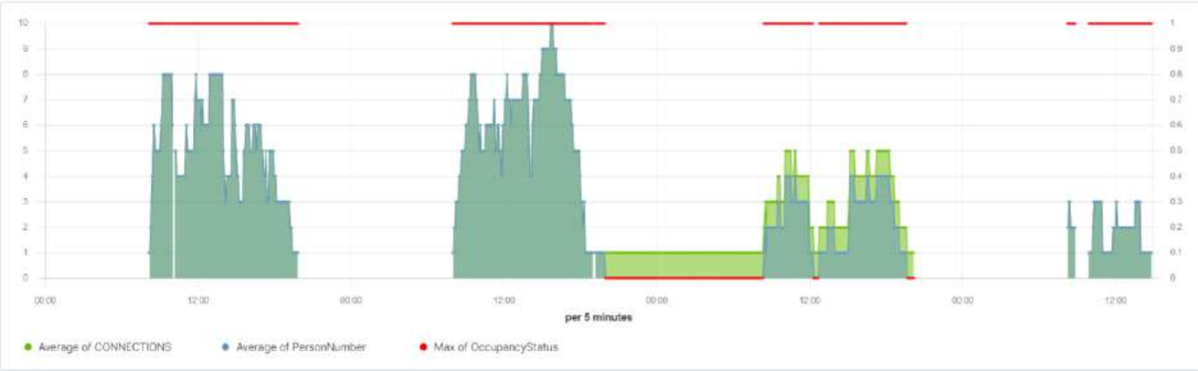


Figure 43: Building's 1st floor South-West area occupancy status data

The number of connections is in light green and the number of persons is in dark green. The corresponding scale is on the left. Most of the time the number of persons is considered as equal to the number of connections. During one night one suspicious connection occurring during the non-working hours is identified. During the following working hours the number of person is scaled down by one unity.

Figure 44:Building's occupancy status data

The number of connections is in light green and the number of persons is in dark green. The corresponding scale is on the left. Most of the connections at the building level are not related to working hours. The occupancy status is in red. The corresponding scale is on the right (1 stands for occupancy and 0 for inoccupancy). The output of Tool 0 feeds Tool 1.

- **Forecast the occupancy status**

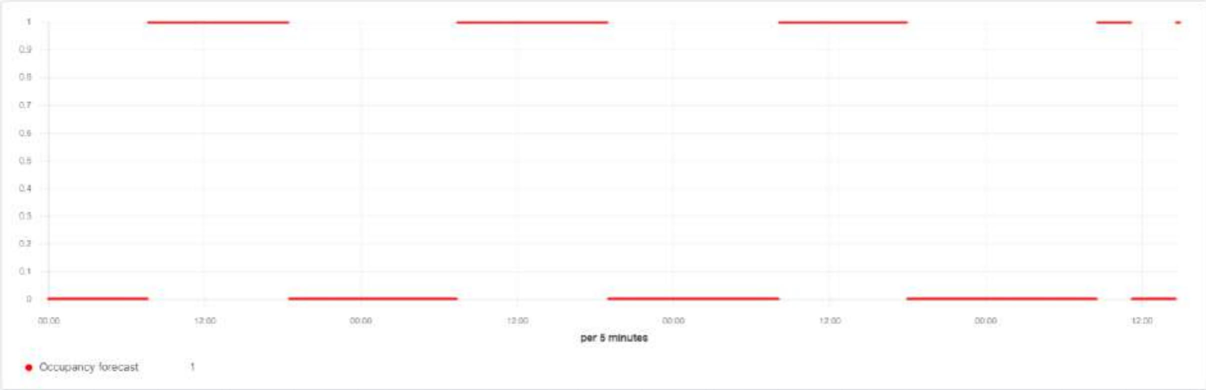


Figure 45: Building's occupancy forecast status 2nd floor South-West area

The occupancy status is in red. The corresponding scale is on the left (1 stands for occupancy and 0 for inoccupancy). In this example the tool forecasts an inoccupancy period during the lunch time for the last day.

- **Projection of the occupancy status for pre-heating and pre-cooling purposes**

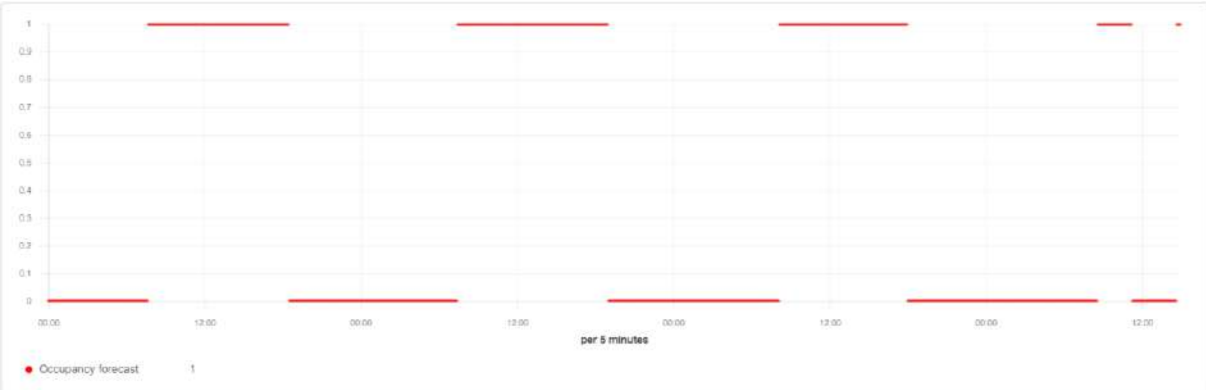


Figure 46: F Building's 2nd floor South-West area pre-heating occupancy period

The occupancy status is in red. The corresponding scale is on the left (1 stands for occupancy and 0 for inoccupancy). In this example the projection of the occupancy status for pre-heating is the same sequence as the forecast of the occupancy status as the running period of the tools in this example was not sufficiently cold or hot to trigger the precooling or preheating in this room.

An assessment has been performed to evaluate the KPIs, and the performance of the tools implemented within this LLUC via the test scenarios below . This assessment is not only evaluating directly the KPIs, but also uses test scenarios to verify that every step of the low-level use case is working properly. All the results are measured only for heating period since the tools updates started during the summer period.

Command sending test

Description	This test aims to verify that the optimization solutions are indeed applied to the building. Commands are sent to the controllers of the buildings, and it is verified that

	they are indeed the actual setpoint of these controllers. No KPI is needed because this test does not need permanent monitoring.
Objectives	Check controllers actually get the command which is sent to them
KPIs involved	None
Results	100%
Notes	The controllers accept the new setpoint for each operational mode, but it is yet possible to choose the mode.

Comfort deviation test

Description	An analyse on the comfort is made to check if the comfort is assured everywhere and at any time in the building. The KPI 1 is a direct evaluation of the comfort regarding to the temperature setpoint.
Objectives	To check if the comfort is maintained in the building
KPIs involved	KPI-1 Comfort during occupancy time
Results	0.22°C
Notes	The heating period since the tools was updated is too short for a relevant evaluation.

Occupancy forecast accuracy test

Description	The use case aims to replace the occupation profile of the controllers with an occupation forecast. This forecast needs to be accurate but even more accurate than the initial profile. The accuracy of both cases are then compared.
Objectives	To check if the occupation forecast is accurate
KPIs involved	None
Results	76% accuracy forecast
Notes	The confusion matrix of the forecast is the following:

		Forecast	
		occupied	inoccupied
Measure	occupied	52	4
	inoccupied	20	24

The accuracy of the occupancy **is 23% better** than the actual occupancy profile accuracy

Gain on heating/cooling consumption test

Description	The use case aims to reduce cooling or heating consumption thanks to an occupation forecast. The energy consumption is measured then analyse to check if the optimization gives a gain on the cooling or heating consumption. This analysis is made by KPI 4 for heating and KPI 5 for cooling.
Objectives	To check if there is gain on consumption.
KPIs involved	**KPI-4 Gain on heating consumption** **KPI-5 Gain on cooling consumption**
Results	None yet
Notes	The new heating program is not used by the building yet. There is then no gain to measure. This test will be performed again early 2023.

Unnecessary heating/cooling emission test

Description	The use case aims to optimize the HVAC cooling or heating emission thanks to an occupation forecast. Thanks to the KPIs 2 and 3, the unnecessary heating and cooling are measured with and without occupation forecast. The measures can be compared to evaluate the impact of the use case.
Objectives	To check if the optimized heating/cooling behaviour is consistent and if the LLUC make an improvement on the unnecessary emission.
KPIs involved	**KPI-2 Unnecessary HVAC heating emission** **KPI-3 Unnecessary HVAC colling emission**
Results	67%
Notes	The heating period since the tools was updated is too short for a relevant evaluation.

The table below summarizes Pilot 3A LLUC01 results.

Table 22: LLUC-3A-01- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1	Deviation to target comfort during occupancy time	0.5°C to comfort range	0.22°C	Validated. The heating period since the tools was updated is too short for a relevant evaluation.
2	Unnecessary HVAC heating emission	<10%	67%	Validated. The heating period since the tools was updated is too short for a relevant evaluation.
3	Unnecessary HVAC cooling emission	<10%	67%	
4	Gain on heating consumption	>10%	-	Not validated. The new heating program is not used by the building yet. There is then no gain to measure. This test will be performed again early 2023.
5	Gain on cooling consumption	>10%	-	

5.3 LLUC-3A-02-Provide demand response services through building inertia and HVAC controls

The use case intends to provide a smart module to supervise the implementation of Demand Response services in an office building using HVAC control and building inertia. This use case aims to:

- Provide flexibility services to contribute to the grid balance (helping to reduce peak demand on the grid)
- Provide accurate predictions of the flexibility available for the next day to help the aggregators to evaluate the Demand Response services provided on the market
- Generate income by contracting with an aggregator

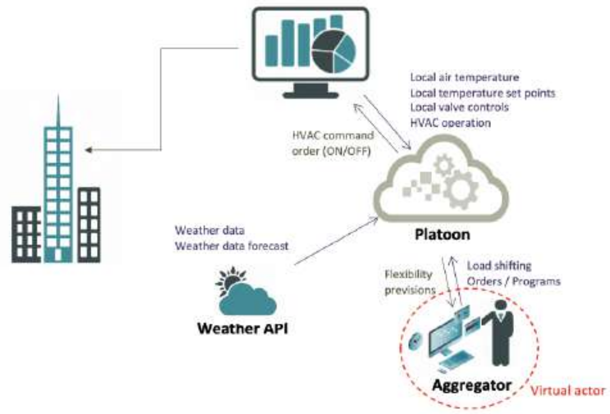


Figure 47: Pilot 3A LLUC02 schema

Challenges were encountered on two levels in the implementation of the LLUC 02:

- The operation of the cooling system feeding the cooling network of the building presented a lot of on/off cycle probably due to oversizing. In this condition it was quite difficult to precisely model the electricity consumption with the start and stops of the system.
- The data regarding heating consumption from the gas counter was updated every hour which limited the resolution of the output data of the model. In fact, it was only possible to predict the energy consumption every hour.

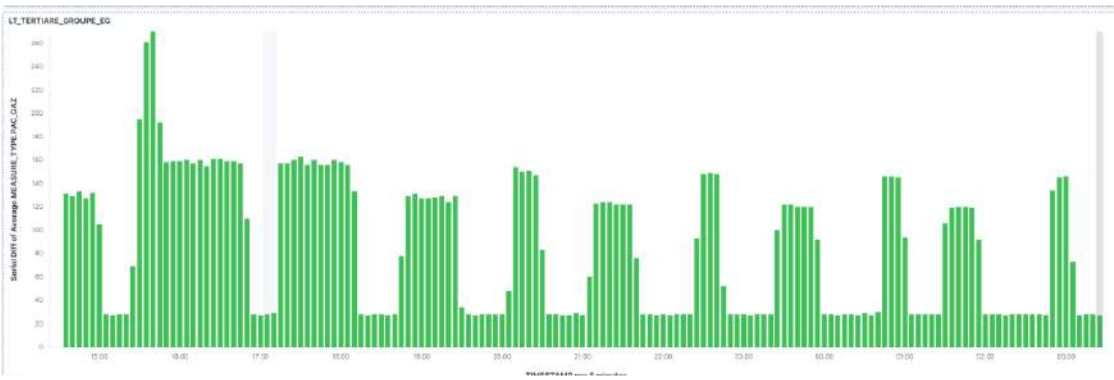


Figure 48: LLUC-3A-02- Energy consumption of the cooling system

As a consequence, the prediction on energy consumption was difficult to perform every 30min as initially planned due to the 2 issues mentioned above.

Furthermore, some of the tools developed for the energy consumption prediction are based as well on the tools of the first low level use case, especially the on the occupancy prediction. Updates on these tools were needed to run more accurately the predictions

5.3.1 Evaluation and Validation

An implementation has been conducted to collect and integrate the cooling and heating consumption data and the integration of the BMS in reading (from data collection) and writing (to send set point to the building) within the platform Pilot 3A were successfully performed. The implementation of the pipelines and the AI services developed within this use case were completed. The parameters and set points to send to the Building Management System were produced and the optimized controls had been successfully sent to the 120 temperature controllers around the building.

As explained in deliverable D4.4 Analytical Toolbox, three services have been developed withing this LLUC to forecast the heating and cooling energy consumption, to assess the load shifting of heating and cooling energy consumption, and to forecast the heating and cooling energy consumption with load shifting potential.
Blow presented un example of the tools results

- Forecast of the HVAC load:

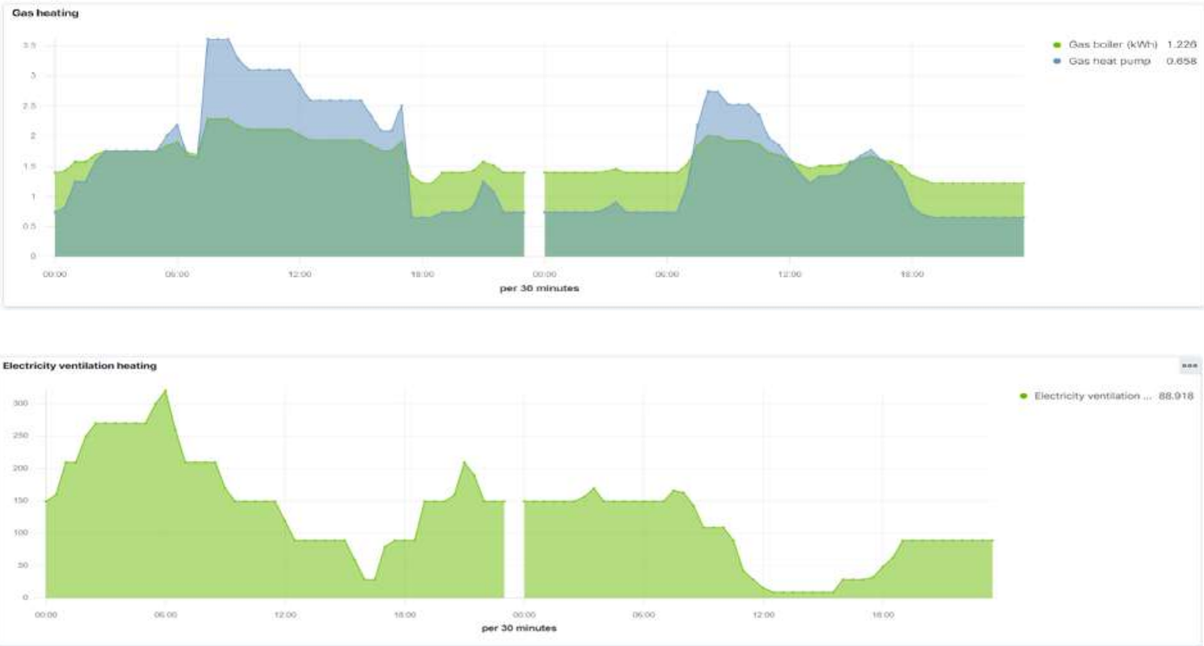


Figure 49: Pilot 3A HVAC Load

The forecasted loads for the main subsystems of the heating system, namely the gas and the ventilation. Energy consumption for gas is kWh and 10 Wh for electricity. Both gas heating system (boiler and heat pump) show less energy consumption during inoccupancy period (during non-working hours). In the heating ventilation system the occupancy status has no impact on the energy consumption, it is only related on the external temperature.

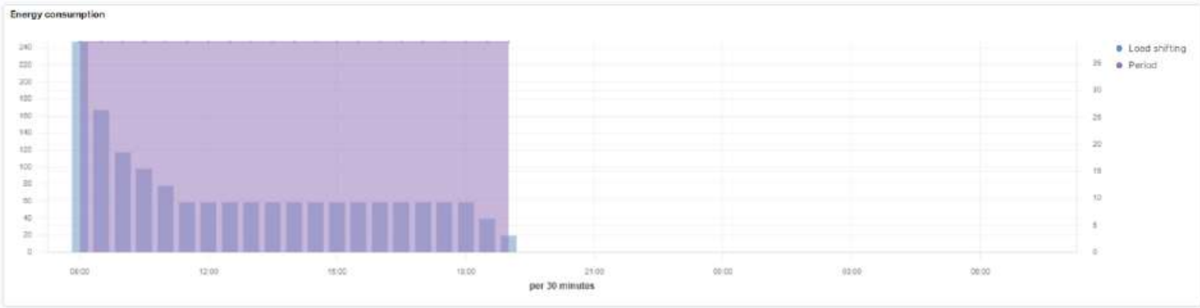


Figure 50: Pilot 3A Load shifting assessement

The load shifting assessment for the next hours shows that the duration of the load shifting, whatever the beginning of the load shifting is equal to the longest period permitted by the tool (38 half hours). In this example the running period of the tool (November 2022) is not sufficiently cold or hot to restart the cooling or heating during the next 38 half hours period. The volume of the load shifting is higher is the load shift begins in the first working hours when the energy consumption is highest of the day.

Figure 51: Heating and cooling load shifting forecast

Tool 3 and tool 5 give the same results as the running period of the tool (November 2022) is not sufficiently cold or hot to restart the cooling or heating during the next 38 half hours period.
An assessment has been performed to evaluate the KPIs, and the performance of the tools implanted within this LLUC02 via the test scenarios below. This assessment is not only evaluating directly the KPIs, but also uses test scenarios to verify that every step of the low-level use case is working properly. All the results are measured only for heating period since the tools updates started during the summer periode.

<u>Consumption prediction accuracy test</u>

Description	The use case aims to make the building flexible. A prediction of the HVAC load is then necessary and must be as accurate as possible. The KPIs 1 and 2 are direct evaluation of the forecast accuracy of respectively the heating and cooling load.
Objectives	To check if the heating/cooling load forecast is accurate
KPIs involved	KPI-1 Mean error on heating load prediction KPI-2 Mean error on cooling load prediction
Results	>300% for heating
Notes	November 2022 had mild temperature so low heating was applied during the training period. Moreover, the heating setpoint in Engie buildings went to 21 to 19°C which trend to overestimate the heating forecast.

Load shifting test

Description	The use case aims to provide demand/response services such as load shifting. The load shifting forecast is essential to assure the demand/response services while maintaining comfort. The KPI 5 measures the load shifting length forecast accuracy.
Objectives	To check if the building is capable of providing load shifting and if the load shifting forecast is consistent.
KPIs involved	KPI-5 Error on the flexibility prediction
Results	None yet (see Notes)
Notes	The test needs an actual flexibility event to be conducted. Engie should get contracted with an aggregator in order to participate to flexibility services.

Consumption saved test

Description	The use case aims to provide demand/response services such as load shifting and so save a part of the consumption. The consumption during flexibility must me know for the load shifting to be valorised. The actual consumption is then compared to the forecast during a flexibility event. The KPI 6 measures the HVAC load forecast accuracy.
Objectives	To check if the consumption forecast during a flexibility event is accurate and consistent.
KPIs involved	KPI-6 Mean error on HVAC load prediction for days with load shifting programs
Results	None yet (see Notes)
Notes	The test needs an actual flexibility event to be conducted. Engie should get contracted with an aggregator in order to participate to flexibility services.

The table below summarizes Pilot 3A LLUC01 results.

Table 23: LLUC-3A-02- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1	Mean error on heating load prediction	Error <10%	>300% for heating	November 2022 had mild temperature so low heating was applied during the training period. Moreover, the heating setpoint in Engie buildings went to 21 to 19°C which trend to overestimate the heating forecast.
2	Mean error on cooling load prediction	Error <10%	>300% for heating	
3	95-percentile error on heating load prediction	<20%	-	Not validated

4	95-percentile error on cooling load prediction	<20%	-	
5	Error on the flexibility prediction	Error <10%	-	The test needs an actual flexibility event to be conducted. Engie should get contracted with an aggregator in order to participate to flexibility services.
6	Mean error on HVAC load prediction for days with load shifting programs	Error <10%	-	

Blow presented pilot 3A LLUC01 and LLUC02 KPIs Dashboard.

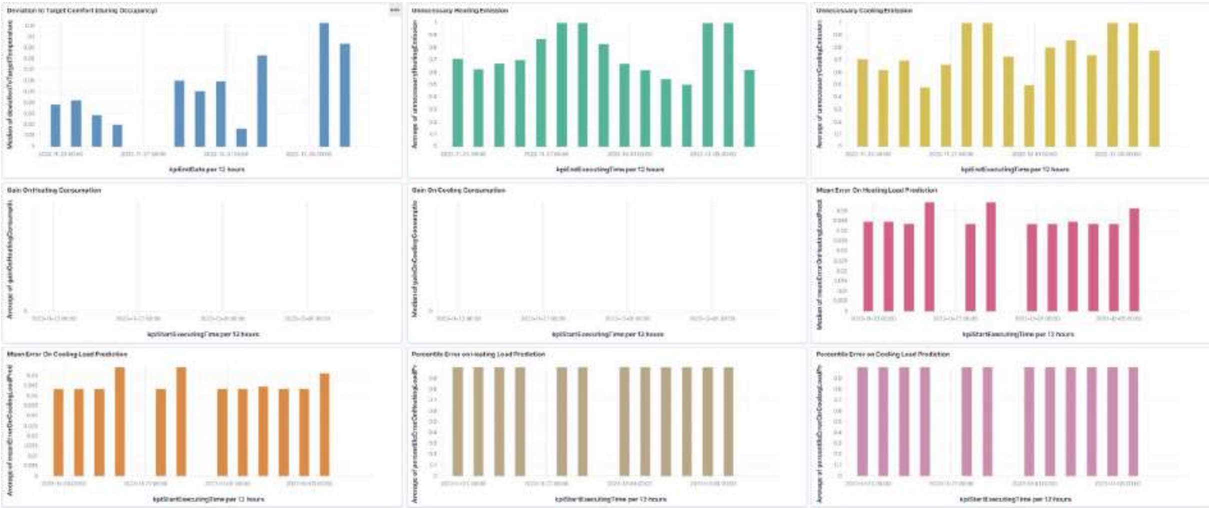


Figure 1 Pilot 3A-02-KPIS dashboard

For now, the new temperature setpoint are not yet applied inside the building. The gain on heating or cooling cannot be measured then. Moreover, the unoccupied period used to calculate the unnecessary heating or cooling does not correspond to the one compute on the buildings controllers. The mean errors get a wrong data index in its calculation which make underestimate the error.
Finally, the deviation to the target temperature is quite low which shows that the building is fully capable to maintain the temperature setpoint even if the setpoint doesn't match with the real occupancy.

5.4 Conclusion

This section presented pilot 3A led by ENGIE tests and validation results for all of the functions and services developed and implemented within the lifetime of the PLATOON project.
The test scenarios associated to Pilot 3A office building operation and performance services validation were conducted onsite, with the support of the Future Building an cities LAB (part of ENGIE research), where the necessary assets and conditions were made available to allow performing, to the extent possible, the pre-defined test scenarios.
The objective set-up to the test phase was to evaluate the technologies developed within the PLATOON project, and to measure their impact on ENGIE's office building thanks to the performance of the occupancy prediction, HVAC load forecast, day ahead pre-heating and pre-cooling schedules as well as flexibility capabilities.

Some of the target KPIs were fully reached, even better than expected for some specific cases where the tests demonstrated better results than the profiles defined for the building. However, some of the tests performed was not enough to evaluate all their associated KPIs, this was due to :

- Inability to assess the energy services during the HVAC cooling operation mode since the tests started after summer,
- Inability to apply yet the new heating program impacting the measurement of the energy gain,
- Updates on the building temperature set points (from 21° to 19°) impacting the HVAC load forecast that trended to oversize the heating.
- Need to contract with an aggregator to be able to participate in real flexibly market as defined which was not able to be done during the lifetime of PLATOON.

All the results have been compiled, reported in pilot 3A section, and consolidated in a dashboard to be continuously monitored by the business. Also, the reasons why some KPIs have not been able to be reached were justified.
To follow-up the pilots evaluation, ENGIE will run new tests early 2023 when the heating system will be used more and another phase during the summer where the cooling system will be operating.
Also, any updates on the pilot's KPIS will be presented during the finale review of the project.

6. Pilot 3B-PI Evaluation & Validation Report

6.1 Introduction

The scope of the Pilot is to create a new way to work in order not only to optimize energy usage and identify behaviours to be changed, but also as an opportunity to reduce maintenance and service interruptions through a better usage of cooling / heating and lighting systems and use algorithms for anomaly detection in HVAC plants. The type of data used in the pilot span from internal consumption data and plants performances to comfort targets managed by user together with external information related to weather forecasts and real time conditions.
The Pilot 3B-PI includes the following use cases:

- LLUC-3B-PI-01- Building Heating & Cooling consumption Analysis and Forecast
- LLUC-3B-PI-02 – Anomaly Detection of cooling & heating plants
- LLUC-3B-PI-03 - Lighting Consumption Estimation & Benchmarking

In order to validate the data analytics tools developed in WP4, the tools have been tested using real data from different kinds of buildings.

6.2 LLUC-3B-PI-01- Building Heating & Cooling consumption Analysis and Forecast

The use case focuses on efficiently forecasting and benchmarking of energy consumption to reduce costs and emissions and improve the comfort of the working environment. For optimization of both cooling and heating systems, it is important to correlate the energy consumption with the occupancy (based on number of employees and customers), as well as to benchmark with similar buildings.

6.2.1 Evaluation and Validation

Table 24: LLUC-3B-PI-01- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1	Deviation between actual and forecasted energy consumption	+/- 5%	[SB] 7%≥KPI ≤40% [MO] 10%≥KPI ≤20% [L102] 8 %	Calculated on real historical data and based on Prophet algorithm. The actual Value is calculated as follows: For every building is calculated the average MAPE (distance between forecast date and calculation date) on 30-day forecasts. The value of the KPI given here is Weekly (YYYY-WW) for each building averaged by cluster (102, Multi-hourly, SB) in order to give a general vision. The Fiumicino office's KPI (L102 Category) was well above the threshold, but it was excluded from the evaluation because the office had major technical problems that had a strong impact on the data produced.
2	Energy consumption gap of a building with itself during the time (year)	+/-10%	From –4% to +2%	Calculated on real data. The business KPI meets the target value. The values of the index are important as it is useful for assessing building performance over the long term **¡Error! No se encuentra el origen de la referencia.**

3	Energy consumption gap of a building with itself during the time (short period)	+/-10%	+/- 24 % (calculated on a building taken as sample)	Calculated on real data. The results doesn't match with the target value, but this is a business KPI. The positive index could be an indicator of something that is not working well in the building. Or can be impacted by unexpected events. The more negative is the value the more is good.
4	Benchmark of a building energy consumption with a cluster of similar buildings	+/-10%	7%	Calculated on real data. The business KPI is useful to compare the behaviour between similar buildings.
5	CO_2 emission reduction	≥ 10%	Annual: From Jan 2022 to Sept 2022 [SB] >10% [MO] >10% [L102] >10% Monthly: -9,20%≥KPI ≤25,82%	Calculated on real data. The KPI is of business type and the value is calculated for each Building. The KPI is calculated on annual and monthly allocated budget for energy and real budget spent. The values represented by the KPI therefore indicate the trend of energy consumption during the year and the corresponding amount of CO_2 reduction

In order to better understand the result of the measurement it's important to highlight the challenge encountered in the implementation of the use case:

- Data availability not as expected
- Buildings with similar characteristics but very different behaviour
- Clusters contain building constructed with different materials
- Standard setpoints for temperatures were changed locally
- Uneven heating and cooling management between buildings with sub-optimal regulation.
- COVID-19: during the covid period, many offices were closed and therefore energy consumption was substantially reduced (historical data)

- Climate anomalies: during 2022, temperature trends significantly exceeded those of previous years and this resulted in higher HVAC usage.

KPI-01 calculates the deviation (%) between the energy consumption forecast and the actual consumption in the building.
The following table shows an extract of the percentage error (MAPE) calculated on the average of the analyzed period from the one-day to 30-day forecast.

	SB FRATTOCCHIE	SB ROMA 40	SB ROMA 114	SB ROMA 162	SB ROMA 107	SB ROMA 132	multioraria ROMA BELSITO	multioraria ROMA TRULLO	multioraria ROMA CINECITTA' EST	multioraria ROMA NOMENTANO	multioraria ROMA EUR	102 DATA CENTER CONGRESSI
	MAPE Average											
Forecasting Day ↓	RML09300	RML28900	RML75200	RML81200	RMP07900	RML89900	RMP01400	RMP01600	RMP02000	RMX01800	RMX10000	RMLA0900
1	23,47%	24,33%	21,08%	32,24%	26,30%	6,95%	17,00%	22,15%	17,96%	17,51%	13,72%	4,05%
2	24,33%	24,79%	21,53%	32,38%	26,49%	7,07%	17,27%	22,42%	18,36%	17,69%	13,81%	4,22%
3	25,42%	25,24%	21,85%	32,60%	26,69%	7,14%	17,19%	22,23%	18,72%	17,75%	14,00%	4,38%
4	26,14%	25,66%	22,21%	32,82%	26,79%	7,17%	17,19%	22,02%	18,97%	17,83%	14,14%	4,53%
5	26,94%	26,26%	22,56%	32,94%	26,95%	7,24%	17,00%	22,39%	19,49%	18,00%	14,35%	4,68%
6	27,86%	26,68%	22,86%	32,95%	26,69%	7,31%	16,60%	22,73%	19,83%	18,16%	14,48%	4,82%
7	28,73%	26,79%	23,34%	33,06%	26,74%	7,37%	16,77%	22,84%	20,23%	18,58%	14,54%	4,95%
8	29,72%	28,42%	23,66%	33,76%	27,65%	7,48%	16,98%	22,48%	20,02%	18,30%	14,38%	5,07%
9	30,55%	28,96%	23,99%	33,65%	27,61%	7,57%	17,02%	22,65%	20,47%	18,38%	14,51%	5,17%
10	31,24%	28,77%	24,28%	33,54%	27,89%	7,59%	17,12%	22,63%	20,85%	18,49%	14,73%	5,27%
11	32,04%	29,43%	24,64%	33,99%	27,95%	7,63%	16,96%	22,29%	21,16%	18,58%	14,89%	5,38%
12	33,03%	30,04%	24,85%	34,06%	27,76%	7,71%	16,83%	21,97%	21,69%	18,72%	14,85%	5,49%
13	33,80%	30,35%	25,27%	34,19%	27,55%	7,76%	16,75%	22,26%	22,03%	18,92%	14,77%	5,61%
14	34,74%	30,64%	25,66%	34,39%	27,50%	7,76%	16,98%	22,07%	22,52%	19,09%	15,01%	5,74%
15	35,57%	32,53%	26,09%	35,09%	28,00%	7,79%	16,93%	21,28%	22,22%	18,43%	14,98%	5,87%
16	36,53%	33,12%	26,56%	35,29%	27,79%	7,80%	16,94%	21,26%	22,42%	18,45%	14,85%	6,01%
17	37,52%	33,20%	26,85%	35,11%	27,64%	7,79%	16,81%	21,26%	22,67%	18,40%	14,73%	6,15%
18	38,46%	33,51%	27,30%	35,00%	27,53%	7,79%	16,72%	21,30%	22,81%	18,37%	14,76%	6,31%
19	39,67%	34,36%	27,81%	35,23%	27,69%	7,80%	16,65%	21,16%	23,19%	18,56%	14,93%	6,46%
20	40,52%	34,77%	28,29%	35,44%	27,67%	7,79%	16,44%	21,30%	23,53%	18,61%	15,12%	6,62%
21	41,67%	34,96%	28,66%	35,66%	27,53%	7,79%	16,74%	21,07%	23,97%	18,96%	15,30%	6,77%
22	42,90%	36,77%	28,99%	36,56%	27,85%	7,72%	16,24%	19,88%	23,77%	18,63%	15,12%	6,94%
23	44,06%	37,20%	29,30%	36,79%	27,68%	7,70%	16,35%	20,14%	24,03%	18,46%	15,21%	7,12%
24	45,17%	37,25%	29,58%	36,51%	27,79%	7,63%	16,31%	20,38%	23,91%	18,31%	15,51%	7,30%
25	46,11%	37,56%	30,02%	36,73%	27,72%	7,57%	16,41%	20,86%	23,58%	18,12%	15,55%	7,50%
26	46,90%	38,32%	30,35%	36,95%	27,65%	7,64%	16,11%	21,15%	23,64%	17,96%	15,48%	7,71%
27	47,35%	39,07%	30,55%	37,07%	27,70%	7,68%	15,66%	21,76%	23,09%	18,35%	15,28%	7,92%
28	48,47%	39,26%	30,87%	36,68%	27,72%	7,61%	15,66%	21,74%	22,22%	18,03%	14,83%	8,13%
29	49,79%	41,41%	31,33%	37,62%	28,41%	7,48%	15,96%	21,00%	21,13%	17,15%	13,94%	8,35%
30	51,00%	42,43%	31,71%	37,79%	28,45%	7,47%	16,01%	20,97%	20,45%	17,44%	13,27%	8,61%
Average	**36,66%**	**32,40%**	**26,40%**	**34,87%**	**27,51%**	**7,56%**	**16,65%**	**21,65%**	**21,63%**	**18,27%**	**14,70%**	**6,10%**

Table 18: LLUC-3B-PI-01 KPI-01 MAPE on Energy Consumption forecasting

The result obtained by the KPI highlights that there is a significative difference in the average values calculated according to building category (Smart Building, Multioraria, DL102).
From the observation of forecasting results we resume that the main factors that can impact on the efficacy of the Prophet algorithm are the granularity of data, the history of the data available for each building category and the intended use.
Infact the "Multioraria" has two 3 years of historical data and the index has an acceptable value. Also, the "DL102" building has a good value index: the presence of historical data, stable environment and not daily human presence could have positively impacted on the results.
The situation of Smart Buildings is more complex. In this case, historical data are short-lived. In these offices, the standard configurations of HVAC systems are changed by the personnel working in the building (according to non-programmable needs.
The following charts show the actual consumption values in blue and the forecasted data in orange dashed line. The grey area indicates the magnitude of error predicted by the forecasting algorithm. Finally, the blue vertical line indicates the point at which the forecast starts.

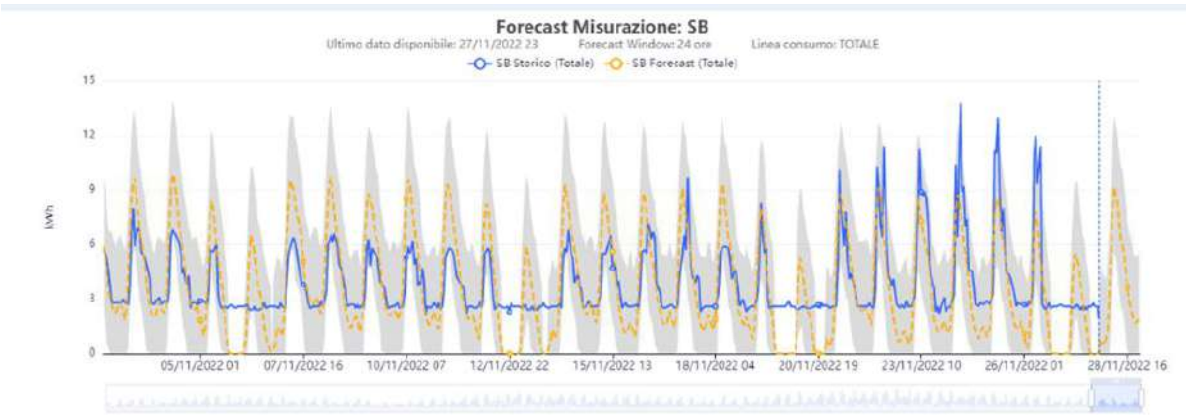


Figure 24: LLUC-3B-PI-01 KPI-01 Energy Consumption forecasting on a selection of Smart Buildings

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53**¡Error! No se encuentra el origen de la referencia.**

Figure 26 shows the comparison of a building's energy consumption compared to the previous year (KPI-02); the green lines indicate the limits of the target value. The business KPI validate the analytic tool because the results are consistent with the data analysed and both allows monitoring of energy consumption and provides useful information for decision support to those involved in defining efficiency strategies or managing buildings.

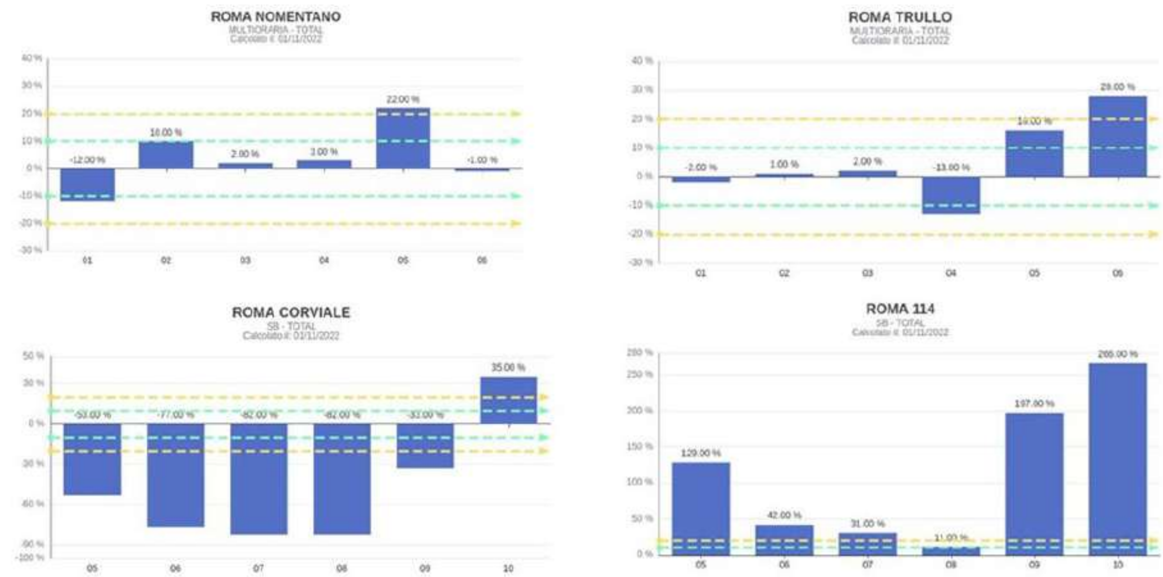


Figure 26: LLUC-3B_PI-01 KPI-02 Energy Consumption Gap of a building with itself during the time

The KPI 03 is based on the benchmark of a building compared to itself on a very short period. The analysis made in November 2022 shows that all buildings have increased their energy consumption in the last two weeks measured (see the two examples in Figure 27). The highest consumption coincides with the period when the heating systems are switched on.

Figure 2: LLUC-3B_PI-01 KPI-03 Energy Consumption Gap of a building with itself during the short period

The KPI-04 (this value is not technical but a business one) compare a building energy consumption with a cluster of similar buildings£

. Measurements show that buildings that have some similar characteristics (climate zone, size, intended use) behave differently. Structural elements of the building (e.g. building materials, glazed surfaces, etc.), exposure and other factors (e.g. human factor) can influence energy consumption, especially lighting and heating/cooling. The tool and the KPI provide valuable support to building and energy managers in making decision.

Figure 26: LLUC-3B_PI-01 KPI-04 Energy Consumption Gap of a building with other building in the same cluster

Finally, the KPI 05 represents the CO2 emission reduction in a year for each building. Also, this is a business KPI so that the target value depends on the action taken by the energy manager to match with the company strategies and objectives. Hence, the validation of the KPI is not based on the achievement of the KPI's target value but on its effectiveness in providing information for the business. Annually, each building is allocated a quota (budget) of monthly expendable Kwh.

The graphics below, taken a cluster of buildings as a sample, shows the energy consumption trend in the period from January 2022 to November 2022. The graph shows that in November, FRATTOCCHIE building consumed 95,85 % of the annual budget. This means that the building will not only exceed the savings targets, but will consume more than the planned budget. The scenario for the building of ARTENA it's very different. In November the consumed budget is 34,19%. So, if the growth trend continues, by December 2022 it is estimated that the CO2 reduction targets will be largely achieved and exceed the defined threshold.

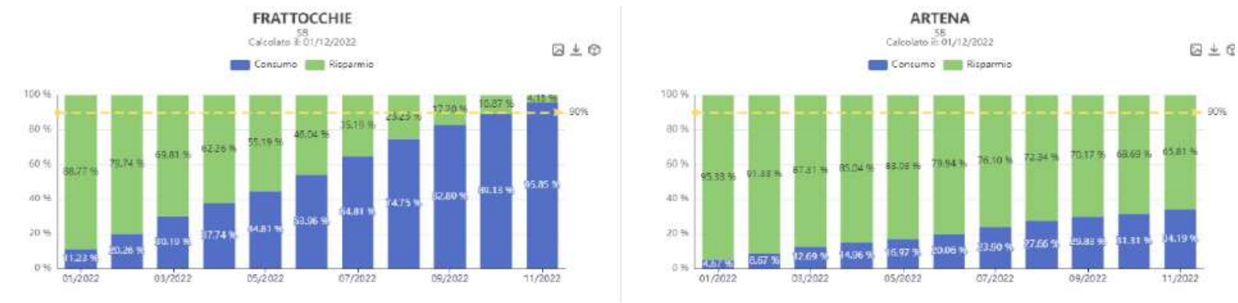


Figure 54: LLUC-3B-PI-01 KPI-05 CO2 Energy consumption trend o the annual budget In the following in the graphic, the CO2 reduction is calculated monthly on the basis of the difference between the allocated Kwh and the Kwh consumed in the period. The dotted yellow lines indicate the minimum thresholds. For example, on November 2022 in Roma 40 building, a CO2 reduction of 18,10% (134,58 Kg CO2) is calculated, while the cumulated C02 reduction from January 2022 to November 2022 is 25,93% (2904 Kg CO2).

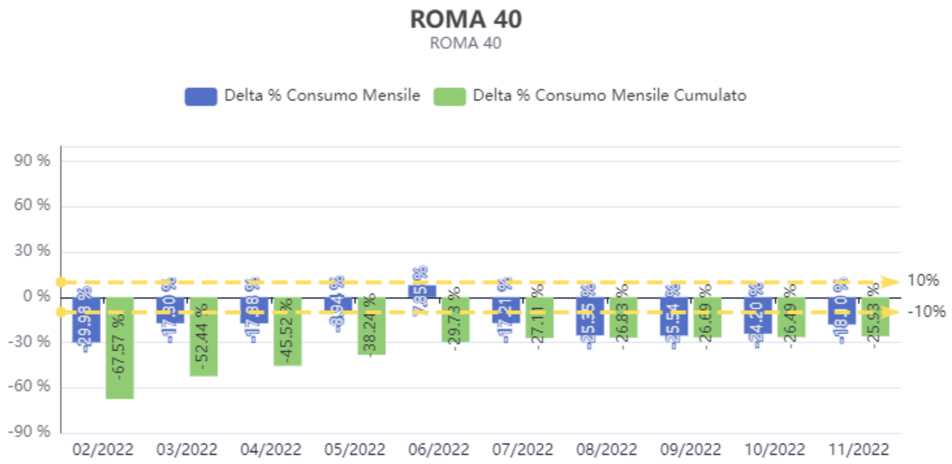


Figure 28: LLUC-3B-PI-01 KPI-05 CO2 reduction trend

6.3 LLUC02-3B-PI-02 Anomaly detection of cooling & heating plants

The objective of this use case is to optimise maintenance efforts through monitoring techniques that can track equipment performance during normal operation and identify anomalies before they result in actual failures.
Based on information collected through meters and sensors installed in the buildings (such as systems energy consumption, internal temperature, number of sensors, …) the app detects possible anomalies in the sensor values, which might indicate a problem on the heating or cooling system.

6.3.1 Evaluation and Validation

Table 25: LLUC-3B-PI-02- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1	Recall – True positive anomalies identification	90%	100%	The anomalies detected by the system are compared to the actual number of anomalies (true positive) occurred.
2	Precision -	90%	100%	The anomalies correctly detected by the system are compared to the total of problematic cases (true and false positive) occurred.
3	F1-Score	90%	100%	The KPI is used in cases where the best combination of precision and recall is desired. F1 score could be used to combine the two criteria. The F1 score is the harmonic mean of precision and recall.
4	Performances Analysis	5%	The calculated index found unexpected values . The target value needs to be reassessed.	The system deterioration index indicates the energy required by the HVAC to maintain the temperature of a building to the optimal conditions per unit of volume and temperature. It is a Business KPI.

During the period of the project the app detected multiple violations of the specified thresholds especially on the temperature sensor measurement on multiple buildings. The analysis has interested a significative set of information.

To validate the Anomaly Detection Tool and KPIs, reports of anomalies, faults and open tickets on Poste's internal systems during the same period of analysis were acquired and analysed. The comparison of the data confirmed the validity of the model.

The following chart shows the detected temperature violation (>27°) for each sensor installed in the building of TRIGORIA.

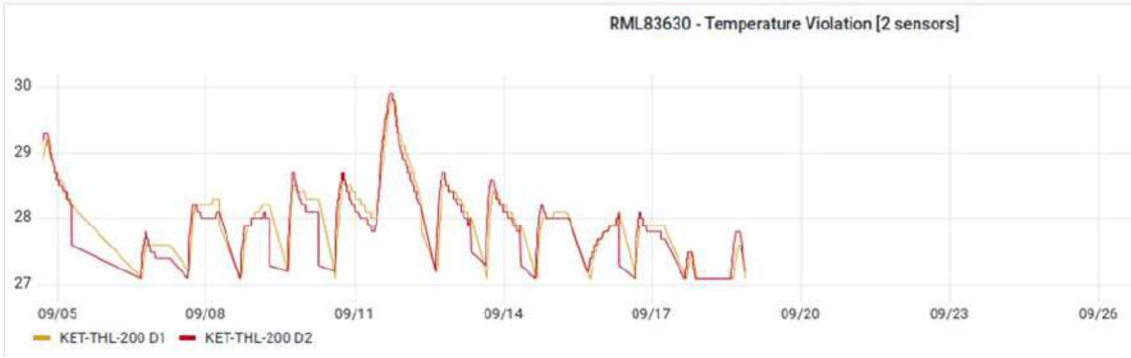


Figure 28: LLUC-3B-PI-02 KPI-01 Temperature Violation in the building of TRIGORIA

The graph below shows energy consumption violations (consumption peaks) compared to outside temperatures; it serves to highlight or justify any increase in consumption due or not due to outside weather conditions. The moments of highest energy consumption (red dots) are concentrated at the time of start-up following the opening of offices.

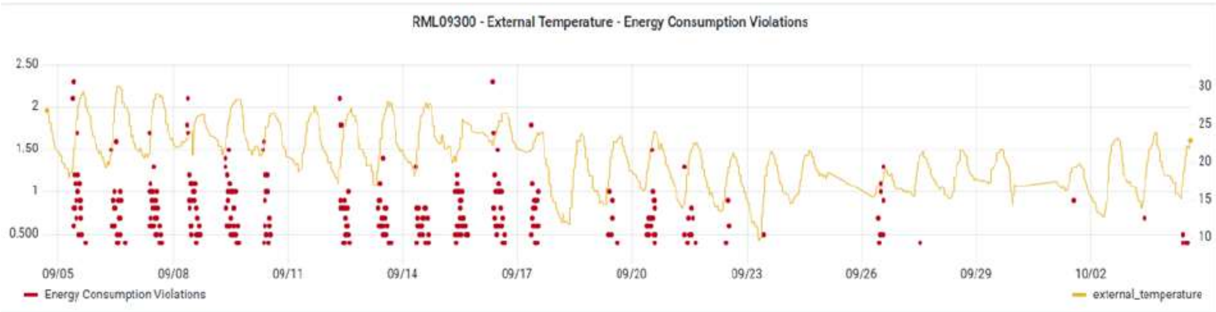


Figure 28: LLUC-3B-PI-02 KPI-01 Anomalous energy consumption peaks in FRATTOCCHIE Building

To calculate the violations, three different methodologies have been applied: rule-based detection, Spikes-based detection (MCOD- Micro-cluster Continuous Outlier Detection) and Trend-based detection which users a Linear Regression approach.

A sample of anomaly result based on Rule-based detection is reported in the following table were the tool reports the events occurred in the building of TRIGORIA, when the temperature is lower (<17°C) or higher (>27°C) than the defined threshold.

RML83630 - Incidents - Rule Based - Temperature

detection_type	incident_time	report_time	value	notes	sensor ↑
DETECTIONRB_EVENT	2022-09-10 21:40:49	2022-10-04 10:56:21	28.50	>27	KET-THL
DETECTIONRB_EVENT	2022-09-10 22:10:49	2022-10-04 10:56:21	28.40	>27	KET-THL
DETECTIONRB_EVENT	2022-09-10 22:25:49	2022-10-04 10:56:21	28.40	>27	KET-THL
DETECTIONRB_EVENT	2022-09-10 22:40:49	2022-10-04 10:56:21	28.40	>27	KET-THL
DETECTIONRB_EVENT	2022-09-10 22:55:49	2022-10-04 10:56:21	28.40	>27	KET-THL
DETECTIONRB_EVENT	2022-09-10 23:10:49	2022-10-04 10:56:21	28.40	>27	KET-THL
DETECTIONRB_EVENT	2022-09-10 23:25:49	2022-10-04 10:56:21	28.40	>27	KET-THL

Table 26: LLUC-3B-PI-02 KPI-02: -Roma TRIGORIA, Temperature violantions in September

The table below shows the anomalies identified in the TRIGORIA Office, using the three methods above described.

General / Detection Incidents for KPIs   Last 30 days CET

RML83630

RML83630 - Incidents - Deterioration Index

detection_type	incident_time	report_time	value	notes	se
DETERIORATION_RA...	2022-07-13 12:45:00	2022-10-04 09:27:53	0.31	2 sensor(...	
DETERIORATION_RA...	2022-07-13 13:00:00	2022-10-04 09:27:53	0.36	2 sensor(...	
DETERIORATION_RA...	2022-07-13 13:15:00	2022-10-04 09:27:53	0.33	2 sensor(...	
DETERIORATION_RA...	2022-07-13 13:30:00	2022-10-04 09:27:53	0.33	2 sensor(...	
DETERIORATION_RA...	2022-07-13 13:45:00	2022-10-04 09:27:53	0.28	2 sensor(...	
DETERIORATION_RA...	2022-07-13 14:00:00	2022-10-04 09:27:53	0.21	2 sensor(...	
DETERIORATION_RA...	2022-07-13 14:15:00	2022-10-04 09:27:53	0.28	2 sensor(...	

RML83630 - Incidents - Rule Based - Energy

building_id	detection_type	incident_time	report_time	value	notes
RML83630	DETECTIONRB_EVENT	2022-07-13 08:28:14	2022-10-04 09:27:28	5.00	>0.4
RML83630	DETECTIONRB_EVENT	2022-07-13 08:43:14	2022-10-04 09:27:28	4.90	>0.4
RML83630	DETECTIONRB_EVENT	2022-07-13 08:58:14	2022-10-04 09:27:28	3.80	>0.4
RML83630	DETECTIONRB_EVENT	2022-07-13 09:13:14	2022-10-04 09:27:28	3.30	>0.4
RML83630	DETECTIONRB_EVENT	2022-07-13 09:28:14	2022-10-04 09:27:28	3.30	>0.4
RML83630	DETECTIONRB_EVENT	2022-07-13 09:43:14	2022-10-04 09:27:28	2.70	>0.4
RML83630	DETECTIONRB_EVENT	2022-07-13 09:58:14	2022-10-04 09:27:28	3.20	>0.4

RML83630 - Incidents - Rule Based - Temperature

detection_type	incident_time	report_time	value	notes	sensor ↑
DETECTIONRB_EVENT	2022-09-10 21:40:49	2022-10-04 10:56:21	28.50	>27	KET-THL-:
DETECTIONRB_EVENT	2022-09-10 22:10:49	2022-10-04 10:56:21	28.40	>27	KET-THL-:
DETECTIONRB_EVENT	2022-09-10 22:25:49	2022-10-04 10:56:21	28.40	>27	KET-THL-:
DETECTIONRB_EVENT	2022-09-10 22:40:49	2022-10-04 10:56:21	28.40	>27	KET-THL-:
DETECTIONRB_EVENT	2022-09-10 22:55:49	2022-10-04 10:56:21	28.40	>27	KET-THL-:
DETECTIONRB_EVENT	2022-09-10 23:10:49	2022-10-04 10:56:21	28.40	>27	KET-THL-:
DETECTIONRB_EVENT	2022-09-10 23:25:49	2022-10-04 10:56:21	28.40	>27	KET-THL-:

RML83630 - Incidents - Rule Based - Humidity

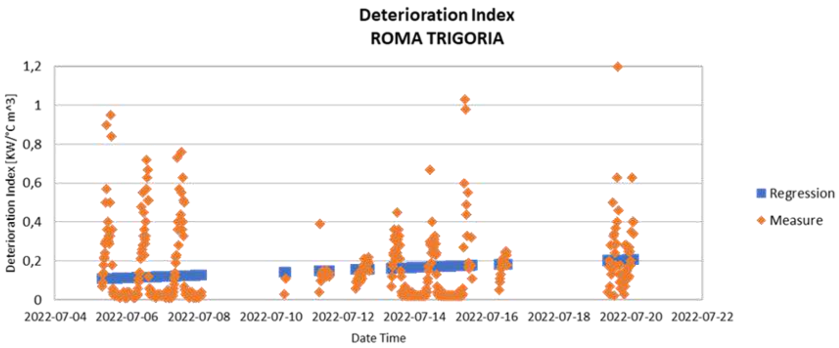
id	building_id	detection_type	incident_time	report_time	val
678...	RML83630	DETECTIONRB_EVENT	2022-09-29 11:40:50	2022-10-04 11:24:52	71
678...	RML83630	DETECTIONRB_EVENT	2022-09-29 11:55:50	2022-10-04 11:24:52	71
678...	RML83630	DETECTIONRB_EVENT	2022-09-29 12:10:50	2022-10-04 11:24:52	71
678...	RML83630	DETECTIONRB_EVENT	2022-09-29 12:25:50	2022-10-04 11:24:52	71
678...	RML83630	DETECTIONRB_EVENT	2022-09-29 12:40:50	2022-10-04 11:24:52	71
678...	RML83630	DETECTIONRB_EVENT	2022-09-29 13:10:50	2022-10-04 11:24:52	72
678...	RML83630	DETECTIONRB_EVENT	2022-09-29 13:25:50	2022-10-04 11:24:52	71

RML83630 - Incidents - MCOD

id	building_id	detection_type	incident_time	report_time	value	notes	sensor ↑	measurement:
58859	RML83630	DETECTIONMCOD_...	2022-08-03 08:15:00	2022-10-04 09:59:23	45.00	R: 9, K 300	EM21CDZ D1,KET-T...	□□□□□□Relative
58860	RML83630	DETECTIONMCOD_...	2022-08-03 08:00:00	2022-10-04 09:59:23	45.00	R: 9, K 300	EM21CDZ D1,KET-T...	□□□□□□Relative
58861	RML83630	DETECTIONMCOD_...	2022-08-03 13:45:00	2022-10-04 09:59:23	44.00	R: 9, K 300	EM21CDZ D1,KET-T...	□□□□□□Relative
58862	RML83630	DETECTIONMCOD_...	2022-08-03 13:30:00	2022-10-04 09:59:23	44.00	R: 9, K 300	EM21CDZ D1,KET-T...	□□□□□□Relative
58863	RML83630	DETECTIONMCOD_...	2022-08-03 12:45:00	2022-10-04 09:59:23	45.00	R: 9, K 300	EM21CDZ D1,KET-T...	□□□□□□Relative
58864	RML83630	DETECTIONMCOD_...	2022-08-03 12:30:00	2022-10-04 09:59:23	45.00	R: 9, K 300	EM21CDZ D1,KET-T...	□□□□□□Relative
58865	RML83630	DETECTIONMCOD_...	2022-08-03 13:00:00	2022-10-04 09:59:23	44.00	R: 9, K 300	EM21CDZ D1,KET-T...	□□□□□□Relative

The following chart show a sample of the results of the "Performance Analysis" (KPI-04**)** executed on ROMA TRIGORIA Building during the months of July and August 2022.

Figure 55: LLUC-3B_PI-03 Violation Detected in RML61900 Building



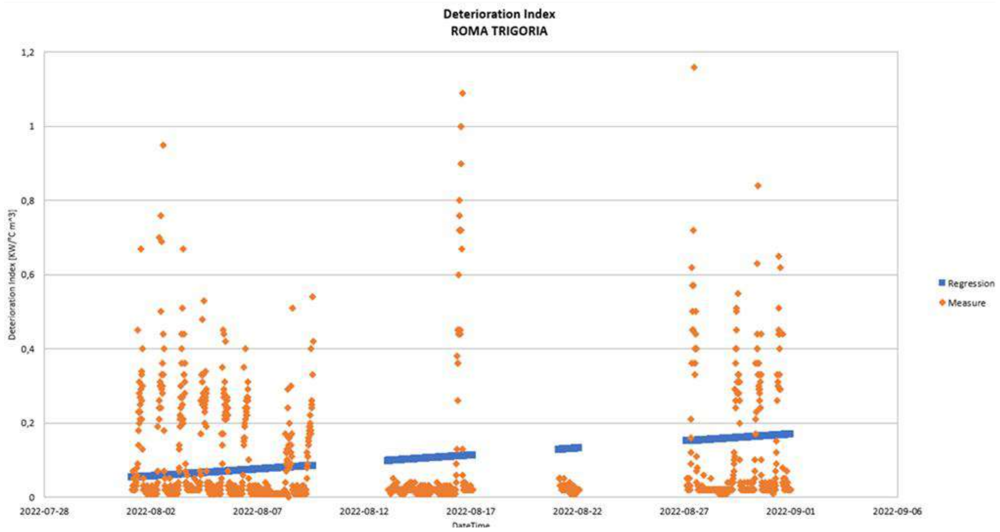


Figure 56: LLUC-3B_PI-02 – KPI-04 Degradation of HVAC Systems

Figure 28 shows a linear regression (blue line) of the performances during each month. In July, the daily average deterioration coefficient of the system was calculated at 0.0067 Khw, while in the following month the value was 0.0037 Kwh. By monitoring these coefficients, the efficiency of the system can be kept under control. The target value currently defined need to be refined to be considered realistic.

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6.4 LLUC03-3B-PI-03 Lighting Consumption Estimation & Benchmarking

The objective of this use case is to estimate the specific building lighting consumption, in order to benchmark, detect anomalies and plan optimization actions to reduce lighting consumption of the building and the corresponding Green House Gases (GHG) emissions.

6.4.1 Evaluation and Validation

Table 27: LLUC-3B-PI-03- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments

1	Lighting Estimation	+/-5%	3%≥ KPI < 16	The KPI calculates the % of deviation between the actual and the estimated lighting consumption.

The information on building lighting consumption is almost never available. The knowledge of the total energy consumption of a building and that of some systems in it is not sufficient to have an estimate of lighting consumption. The app calculates this value starting from information on consumption but analyzing also other information and produces the value required. To test the validity of the algorithm, an analysis on buildings with the lighting consumption information (classified as Smart Buildings) was performed and instructed the algorithm to make an estimate. The estimate is compared with the actual data. As shown in Figure 59 the KPI has a value of 15% with a deviation of +2% from the threshold value.

Figure 59: LLUC-3B_PI-03- Lighting Estimation

The benchmarking service provided near real-time information to the energy manager giving immediate and objective feedback on the effectiveness of the chosen solution that led to a significant reduction in consumption.

6.5 Conclusion

Compared to the use cases identified for the 3B-PI pilot, the tools developed, although simple, provide a valid support for end users in the energy domain (building and energy managers) to monitor, in some

cases almost in real time, consumption trends and the behavior of HVAC and lighting systems as external or internal conditions change, even unexpectedly.
The analysis method developed for the forecasting of energy consumption (LLUC01) and lighting consumption (LLUC03) showed that in the presence of scarce historical data, the margin of error become significantly high. The remaining KPIs calculated for the LLUC01 measure business performance and thus provide useful elements for performance monitoring and decision support. A margin for improvement can be considered for the Benchmark service in calculating KPI-04 by introducing others elements of comparison into the analysis. During the pilot, possible further data useful for improving KPI-04 were not available, but from the analyses made, such data were identified.
The Anomaly Detection Tool (LLUC02) has been integrated into the Digital Enabler platform and, even if tests have been performed in a short time, has demonstrate a reliability in the results.
In general, since the algorithms are based on trend analysis of historical data, we believe that the influence of the COVID-19 event (consumption was drastically reduced due to office closures) and the subsequent weather situation, which, with the abnormally hot weather, led to higher consumption of air-conditioning systems, altering the consumption scenarios of previous years, should be taken into account when evaluating the results of the analysis.

7. Pilot 3B-ROM Evaluation & Validation Report

7.1 Introduction

This pilot is formed by 1200 buildings owned by the municipality of Rome and focuses on the Monitoring and Analysis System of Data coming from energy meters (power and gas) of these buildings large asset. The main scope is to integrate several datasets into a unique advanced energy management system with a spatial approach, in order to fasten the internal processes and workflow of the SIMU Dept. of Rome Municipality offices, so facilitating the detection of **anomalies**, the **periodical Reporting**, both for historic and forecasted data, and the **RES potentialities assessment**.

The Pilot is divided into four low-level use cases:

- LLUC-3B-ROM-01 – Spatial reporting,
- LLUC-3B-ROM-02 - Benchmarking,
- LLUC-3B-ROM-03 – Forecasting
- LLUC-3B-ROM-04 – RES potentiality (PV plants)

Each of the low-level use cases corresponds with a Service implemented through a dedicated Dashboard of the web Toolbox and a series of correlated datasets, collected periodically.
The type of data used in the pilot span from energy consumption data for power (6500) and gas (2500) meters, heat flux counters (2500), buildings structural data, PV plants (160) energy production and self-consumptions potentialities from RES, together with external information related to weather forecasts and real time conditions.

The use of data curation and treatments tools, offered by the DE pre-analysis component, will consent to design connectors from data sources, reducing costs and time when these sources change depending on new energy supply contracts.

One of the main lessons learnt, implementing and assessing the Pilot, is represented by **the critical impact of the variability and heterogeneity of the datasets provided by Energy Services Supplier** for a typical large asset of buildings. Policies for tenders can change and these services could be aggregated (unique buildings lot or few lots) or disaggregated (many contractors for buildings lots), based on short term (1 or 2 years) or on mid-term (5 – 7 years) contracts and the tenders could be extended to all or some energy vectors and appliances. To face this critical issue, designing and maintaining an advanced EMS three main strategies can be adopted:

1. **Enabling a data collection and pre-treatment fast procedure** to ensure the data curation within a pre-treatment environment (section of DE adopted in the pilot) able to standardize and integrate datasets, each time new sources are activated, to feed the analytical toolbox. In this approach the pre-analysis phase takes time and the improvement of semantic data could play a crucial role, although dealing with fragmented data sources results in major effort in the initial phase to minimize meta-data and relation errors. Training this part of the toolbox architecture with many different data sources will produce a progressive reduction of the time needed to process the new items.

2. **Fast implementation of data connectors** for each of the different data sources, considering that often the Energy Vendors will not consent to run code or programs on their servers to push data, so passive connectors should work on browsers pulling data from the suppliers portal services or on periodical mailing with automatic forwarding to the DB repository. This approach consents to build a semi-automatic data flow, supporting and accelerating the data collection (1), but connectors will likely become obsolete within few years. The activity of the 2nd Open Call winner (APIO, see WP7) for the pilot 3b-ROM focused on this solution: a connector has been established for the Heat flux Sensors Data on the Energy Service Supplier CPL-EFM server and an automatic mail forwarding to the Pilot repository has been set for the new Power Energy Supplier HERA.

3. **Independent IOT solutions**: Design and implementation of direct nRT Data flows from the meters working independently from the energy suppliers and vendors. This approach foresees a relevant initial investment when dealing with thousands of meters (6500 power + 2500 gas in the pilot 3b-ROM) but the test made on 15 power meters in the last phase of the WP6 and WP7 demonstrated that with the new generation of smart meters the cost for the needed extra IOT devices drastically decreased. Once such a system will be implemented and maintained the data analytics Toolbox will receive a stable energy data flow, and the data coming from external suppliers can be used for periodical confrontations.

The pilot offered the opportunity to test and verify the three strategies above described, facing not only the technical issues but also the governance and decision procedures. The relations with the suppliers (ENEL, HERA), the DSO (ARETI, ITALGAS), the Concessionaries (CPL and its contractor for data management, EFM) and above all with the decision makers within the involved departments in the Municipality of Rome, significantly slowed down the work phases. The third strategy making more independent, robust and stable the overall application could be considered the ideal solution for enhancing any advanced EMS serving a large asset owner or manager, that's why in the very last phase of the Pilot, with the support of the 2nd Open Call winner APIO two connectors have been tested for the big-data source of the Heat Flows Sensors (2500 already installed and monitored by CPL-EFM) and for 15 selected and representative power meters. In this second test dedicated IOT devices were installed and Chain2 data transfer was activated from last generation meters. The evaluation of this sub-pilot is presented within the WP7 DLVs.

7.2 LLUC-3B-ROM Monitor and analysis of data coming from energy meters of ROME Municipality buildings asset

The four services compose an integrated monitoring and analytical system for data coming from the meters (power and gas) of the non residential buildings asset of the Rome Municipality and aim to increase the awareness on the energy consumption profiles, anomalies, forecasting, PV plants potentialities on roofs and more in general on the efficiency measures potentialities.

The toolbox includes a rapid energy audit tool determining the Energy Performance of buildings, that can be applied to the whole asset, and two innovative forecasting algorithms (Prophet by ENG and DeepAR by BUILTRIX, 1ST Open Call winner) are implemented offering the opportunity to compare the results.

The pilot can also increase the capacity of the Energy Management office to produce more frequent and accurate Energy Audits including a standard Energy Performance (EP) analysis for each building. At present, the Energy Audits for some sets of buildings where produced with a traditional approach, within tenders delivering just PDF documentations and not-mainstreamed information that typically result soon out-dated. The four Platoon services all together contribute to speeding up the energy audits, turned into a continuous process, where, with no further costs for the Department, baselines and forecasts can be updated and the PV implementation potentialities for each roof can be integrated with current self-consumptions and RES exporting capabilities (Energy Community scheme). The added value consists in the advanced digitalization and semi-automation of the energy analysis, with a strong spatial approach, in the direction of continuous data management, even from heterogeneous sources, to build and exploit an integrated DB for the EMS of the municipality large asset.

Furthermore, the integrated organization of the datasets coming from different sources, previously fragmented in terms of management and assessment, within the DE architecture accessible via a unique Toolbox represents a relevant added value for the SIMU Department (Plant UO) and for the ROME City Data Platform (CDP, today a work in progress holistic platform) which aims to make a multiplicity of data accessible and transparent for citizens and stakeholders. Pilot-3b-ROM will provide to the CDP the pre-processed big data for energy dedicated to the municipal non-residential asset.
The evaluation of the pilot can be run at different levels: (A) energy planning and policy level; (B) information and data quality level and (C) energy efficiency technical level. Most of the KPI presented are focusing on the (C) energy efficiency technical evaluation, although some concerns the (A) energy management level.
It is important to notice that the Dashboards corresponding to the 4 services are used by officers with specific competences and tasks to achieve, that will be logged and will find in the *Notification Area* of the toolbox the functionalities to report and comment their work sessions, to propose the efficiency or maintenance measures to be implemented and to receive automatic notifications based on pre-set

criteria (i.e. setting a rule set for anomalies detection for a subset of buildings). In order to analyse and assess these notifications, consisting in an adequate volume of sessions, it will be necessary to wait 6-9 months after the end-users begin to use the platform on a regular base.

The PV potentialities service includes several tools, mainly developed by BUILTRIX, to assess the PV plants energy production, current and potential considering the extension of the plants that can be hosted on the free surfaces of the same roofs. Based on the spatial analysis of the roof and the physical installations, it presents PV maximum Peak Power and energy yearly production installable, its costs, incentives, ROI, self-consumption and energy savings results, offering an overview for each building of the RES optimal exploitation in view of the adoption of the new scheme related to the Renewable Energy Communities – REC – promoted by the RED2 EU Directive.

The use of the PV potentialities service allows officers to produce efficiency scenarios that enrich energy audits by promoting the expansion of the municipality's photovoltaic park, maximizing self-consumption and the production of excess energy that can be shared with other users under the new local RECs, moreover in line with the institution's recent strategies (SECAP of Rome 2020-2030).

7.2.1 Evaluation and Validation

Table 28: LLUC-3B-ROM- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
01	Total Energy Savings TES KPI01a : [kWh / y] (Derived TECS KPI01b: [€ / y]) [% : kWh-saved / Tot. kWh-Yc] [Yc current year = past 12 months] This KPI can be analyzed distinguishing: KPI-01-power	1 % =relevant; 2 % =good; 3 % =very good; Over 3% =excellent Baseline 2021: Total consumption= 87.000.000 kWh Total yearly cost = 30.450.000 Euro	the Total Energy Savings [%] calculated and limited to interventions resulting from the toolbox use (test phase: 4/21 – 4/22) **is 1.1%** **between 1% and 2% (Good).** This result comes mainly from measurable EVENTS: Anomalies in energy invoices detected and corrected using Platoon benchmarking service (extra costs: 180k€, equivalent to 514.000 kWh); Four large buildings with very low	The analysis of the meters data (historical and current) produces a series of measures that should reduce the yearly total energy consumptions, such as direct efficiency interventions, dismission of un-useful meters, maintenance and rehabilitation plans on buildings following consumptions anomalies detection. A derived KPI-01b is the Energy Cost Saved (€/y) that depends on energy tariffs but could be also impacted by contractual (or invoices) re-definition resulting from the use of Platoon data analytics toolbox. A list of the EVENTS (actions/interventions) impacting on TES, will be provided

	KPI-01-gas		performance detected with the toolbox have been included among the efficiency measures in next year's planning (saving for around 443.000 kWh and 155k€); **Total Saving: 957.000 kWh for 335k€**	periodically and can be annotated by the users within the toolbox.
02a	Saving Costs Personnel costs (Euro/y) Or % (use % if total cost of the personnel on related task is known)	Non relevant <1k€ Up to 10k€ = relevant Up to 30 k€= good Up to 60 k€ = very good Over 100 k€ = excellent [Personnel Hourly cost X Total hours of work avoided in the year]	This KPI calculation should base on specific reports on employees by the SIMU offices, but in this phase the KPI can be estimated through users interviews: the recent user tests results estimate the **saving in personnel cost is Relevant (around 8 k€)** considering that in 2022 the use of the toolbox has been quite limited.	The use of the toolbox and the automatization of some functionalities offered by the 4 services will decrease the amount of worked hours dedicated to the same tasks, freeing up time for other activites. The installation of a nRT monitoring systems (tested in WP7 recently) is going to further reduce the costs for the personnel, mainly impacting on the activity of control of the correctness of the energy bills.
02b	Saving Costs Energy Related Costs other than 2a (Euro/y)	Relevant: >1000 Euro/y Could be included in KPI02a targets; Other Cost Savings resulting from the use the 4 services offered by the toolbox	Among the recorded EVENTS (5/21 – 5/22) we find the Dismission of 20 meters with zero consumptions, generating a saving calculated summing the **fixed fees avoided (Relevant : around 12k€/y).**	This component of cost saving refers to costs other than personnel. i.e. fixed fees paid for meters that have to be dismissed as a result of the toolbox services application. Note: this is NOT the Cost for Energy Saving that is derived from KPI_01
03	Nb of Meters with Energy Savings Results (Nb of Meters)	Non relevant <1 Up to 10 =relevant; 11-30 =good; 31-60 =very good; Over 60 =excellent	Counting the Nb of meters impacted by Platoon toolbox, during the users test phase, gives the **result for this KPI (Good: 23 Meters**	This indicator counts the number of energy meters for which PLATOON data analytics tools produce some action resulting in energy saving during the year.

		To be calculated on the basis of KPI-01 and KPI-02b analysis.	**positively impacted by Platoon toolbox).**	Derived KPI: KPI01/KPI03 represents the average energy saved [kWh] per meters involved, and measures the average intensity of the single EE interventions
04	Nb of Anomalies detected (Nb of Recorded Anomalies In the Notification Area of the toolbox)	10 =relevant; 11-20 =good; 21-30 =very good; Over 30 =excellent	**Good Result = More than 20 Anomalies detected ;** A list of detected anomalies identified through the toolbox will be annotated by the users in the Notification Area, in order to progressively measure this KPI.	Not all alerts sent by Platoon tools produce Energy Savings therefore it is interesting to track separately the Number of Anomalies occurred during a period of observation. The definition of Anomaly for a specific energy meter is based on the occurrence of the consumption divergence from the expected value (benchmark analysis), in the same period. Typically when the building itself or is usage is highly inefficient Platoon will send a series of alerts. This must be considered a good result of the project even if the beneficiary is unable to intervene producing energy savings.
05	CO2 emission reduction	Same criteria for KPI-01 Target	**248 tons CO2 avoided** **Result = Good**	See Indicator n.01 comments. Apply the specific Conversion Factor (in this case, 258,63 g CO2/kWh for Rome and Power Energy)
06	RES suggested self-consumptions (kWh/years) Or Extending calculation to the maximum RES production that can be installed on the roof when planning a plant within the REC	Over 130.000 =relevant; Up to 400.000 =good; Up to 800.000 =very good; over 1.200.000 =excellent Rom_04_Kpi_R06 is an additional component to ROM_04_Kpi_01 as it represents	**Result= excellent both** **for 4.800.000 kWh/y** based on RES suggested self-consumptions **and** **for 10.200.000 kWh/y** based on the calculation of the maximum RES production, within the REC scheme promoted by the Municipality	The calculation of the RES potentiality is based on the energy from new PV plants that can be installed on municipal roofs, is based on the load curves, on the availability of irradiated surfaces to install RES plants, their tilt/orientation, BOD (using PV-GIS JRC model). It includes the self-consumption energy quote that depends also on RES/Storage solutions

	(Energy Communities) scheme, where also the exceeding energy is shared with other proximity meters.	the potential further Energy saving (self-consumptions) and new local RES production	Calculated through the toolbox on the new potential PV plants that can be installed on municipal roofs.	that can be foreseen (toolbox settings). Platoon output in terms of Total Potential RES [kWh/Y] calculation represents the positive impact of planned installations.

07	Nb of Tools Outputs
	
	(Number of occurrences from Toolbox log)
		Over 100 =relevant;
		
		over 200 =good;
		
		over 400 =very good;
		
		over 600 =excellent
			Result= Good
			
			For 242 tools outputs
			
			Calculated counting the outputs coming from the Platoon Toolbox for Pilot-3b-ROM during the user test phase (12 months).
				Platoon results in terms of Queries with Output processed by the offered (tested) tools represents a positive impact to be measured. Measuring the usage, this KPI is referring about the effective engagement of the ROM personnel.
				Counting outputs for each distinct services and tools will help to address further development and exploitation strategies.

08	Vote assigned by the Test Users 7 assessment criteria are: Layout, Intuitive use or usability, Usefulness, Use Frequency estimated, Workflow improvement, Impact on optimization of their task, Impact on Energy Efficiency	Target: >6 Range [0 – 10]	**Spatial Reporting = 6.8** **Benchmarking = 6.7** **Forecasting = 5.7** **PV Potentialities = 6.2** See Figure below for more details.	Calculated at the end of the final User Test phase, where 10 Officers assigned a vote for each services a for each of the 7 assessment criteria They also answered a questionnaire pointing some priority improvements that could turn the services more suitable with their work and expectations. In particular for Forecasting (S3) a rating under the sufficient target depends on the scarce usability and consequent low impact on workflow (need for more clear Forecasting Reports).

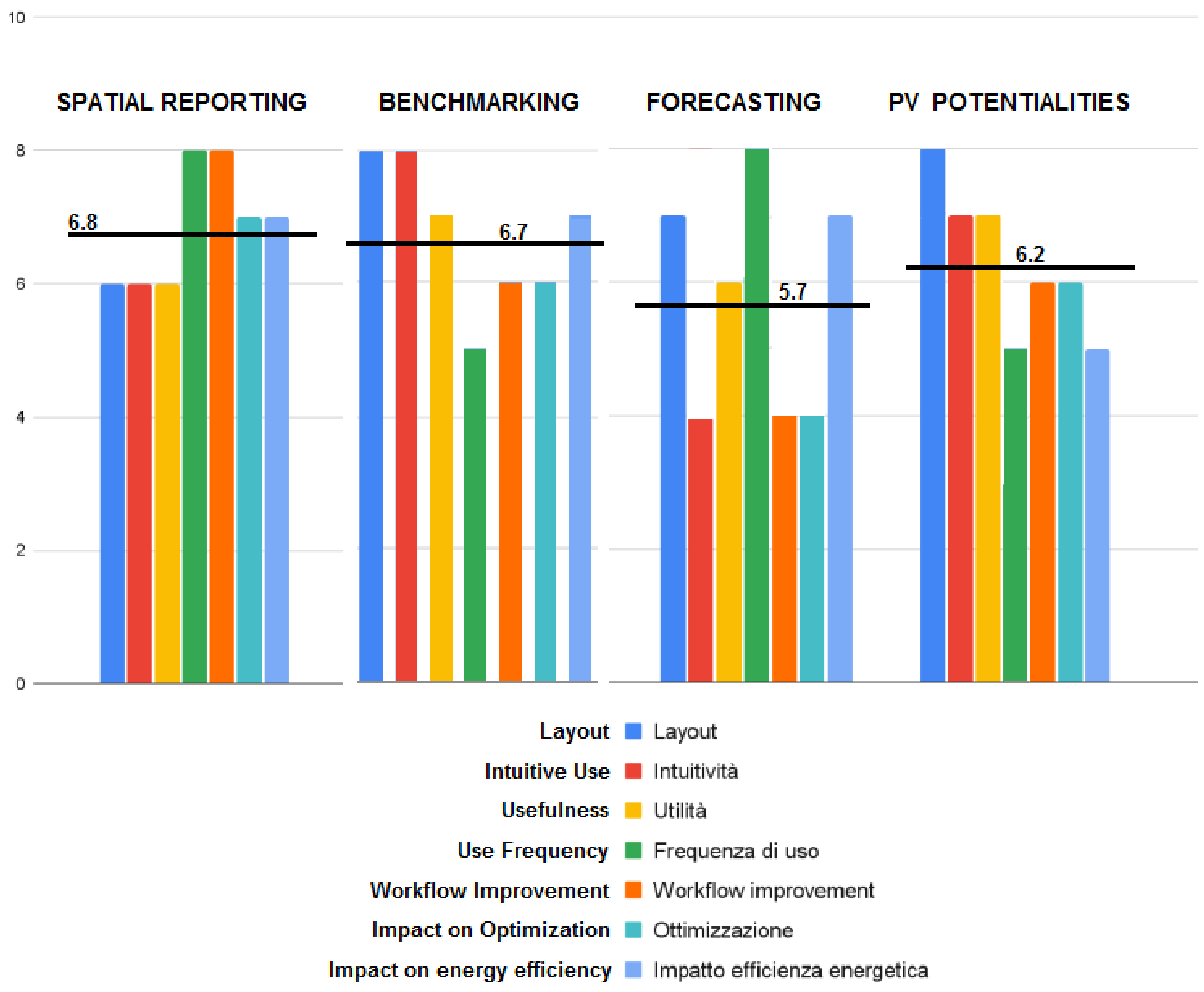


Figure 60: Results of the User Test for each Service of the Pilot-3b-ROM toolbox

- **LLUC-3B-ROM-01 – Spatial reporting**
  This use case focuses on buildings and complex of buildings placed on the Rome Municipality map (15 Districts called *Municipi*) and consents the selection through text search or spatial query or structured menus in order to aggregate energy data coming from buildings, both for power and gas consumptions. Here it is also possible to show structural and dimensional data describing the buildings and their main uses.
  The integrated monitoring and analytical system for data coming from the meters of different buildings of the Rome Municipality and from specific areas (Districts or smaller) is going to increase the awareness on the energy consumption helping the ROM officers to identify efficiency measures and priorities assessing consumptions profiles and spatial distribution.
  The KPI_01 and the KPI_02 were calculated after a period of test use of the toolbox, when each concrete action contributing to the Energy Savings has been traced by the officers. For example, dismissing n.20 power meters on the basis of the toolbox analysis impact mainly on Money Saving (KPI_01, Euro/y) and on reduced Personnel cost (KPI_02, €/y); Alert on excessive consumptions on 4 large buildings coming from benchmarking and forecasting tools helped orienting next planned energy efficiency interventions, resulting in Energy Saving; Anomaly

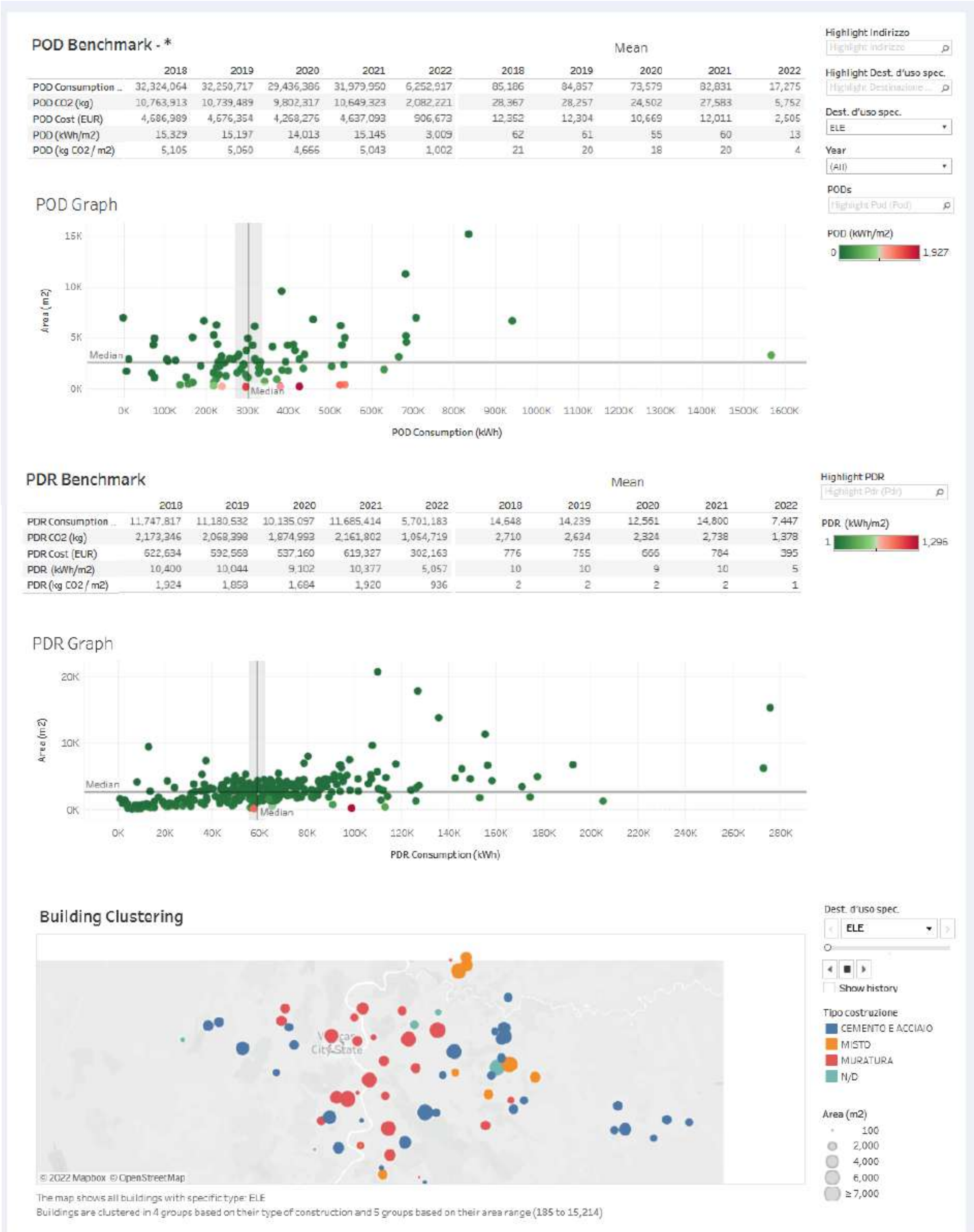
detection in benchmarking could also highlight a serious error in invoicing compared to expected consumptions , resulting in a fast opposition versus the vendor and consequent repayment (Energy Costs Saving).

More in general a list of actions and planned interventions, resulting from the pilot Toolbox use, delivered at the end of a period of use of the tools consents to calculate KPI_01 (and some derived KPIs), KPI_03, KPI_05, KPI_07.

Figure 36: Pilot 3b-ROM-01 – Spatial Reporting dashboard: 1200 buildings with power and/or gas meters supplying data to the toolbox. The queries and spatial selections offered consent to obtain partial aggregated reports per Districts or per typologies of buildings.

Figure 36 : Pilot 3b-ROM-01 – Spatial Reporting dashboard: overall energy consumptions from Gas Meters annual data and Power Meters annual data, for the whole analyzed asset. The same can be done for clusters of buildings based on several selection criteria.

The KPI_02 (Personnel cost saving) and KPI_08 (Votes by test users) have been presented specifically for this service. The automated reporting functionalities seems to be at present among the most appreciated outputs reducing significantly the time users have to dedicate to this task, although it was not possible to calculate precisely the Personnel Cost Saving without the specific hourly costs of the designed officers.



	2018	2019	2020	2021	2022	Mean 2018	Mean 2019	Mean 2020	Mean 2021	Mean 2022
POD Consumption ..	32,324,064	32,250,717	29,436,386	31,979,950	6,252,917	85,186	84,857	73,579	82,831	17,275
POD CO2 (kg)	10,763,913	10,739,489	9,802,317	10,649,323	2,082,221	28,367	28,257	24,502	27,583	5,752
POD Cost (EUR)	4,686,989	4,676,354	4,268,276	4,637,093	906,673	12,352	12,304	10,669	12,011	2,505
POD (kWh/m2)	15,329	15,197	14,013	15,145	3,009	62	61	55	60	13
POD (kg CO2 / m2)	5,105	5,060	4,666	5,043	1,002	21	20	18	20	4

	2018	2019	2020	2021	2022	Mean 2018	Mean 2019	Mean 2020	Mean 2021	Mean 2022
PDR Consumption ..	11,747,817	11,180,532	10,135,097	11,685,414	5,701,183	14,648	14,239	12,561	14,800	7,447
PDR CO2 (kg)	2,173,346	2,068,398	1,874,993	2,161,802	1,054,719	2,710	2,634	2,324	2,738	1,378
PDR Cost (EUR)	622,634	592,568	537,160	619,327	302,163	776	755	666	784	395
PDR (kWh/m2)	10,400	10,044	9,102	10,377	5,057	10	10	9	10	5
PDR (kg CO2 / m2)	1,924	1,858	1,684	1,920	936	2	2	2	2	1

Figure 37 : Pilot 3b-ROM-02 – Benchmarking dashboard: overall energy consumptions, costs, CO2 for both Gas and Power meters and clustering of buildings by type of construction

- **LLUC-3B-ROM-02 - Benchmarking**
  Within the benchmarking service is included the High-Level Anomaly Detection functionalities but these need to be further tested and used by the ROM officers in order to implement the specific rule-sets and thresholds that will define the anomalies conditions.
  Basically the automatic benchmarking analysis presents buildings that exceed their reference cluster parameters. The main assessment can be done in terms of performance (KWh/sqm) through a graphic interface that highlights buildings that exceed the average value, orienting and supporting the user in the search for technical causes and in the definition of response measures.
  POD (electricity) and PDR (gas) benchmarking can be aggregated for each building or complex of building.
  At the end of the Users test phase (M35) the KPI_04, the KPI_07 and the KPI_08 can give a picture of the usability and effectiveness of this service. A margin for improvement for the calculation of these KPIs is possible by introducing new elements of comparison into the analysis, aiming to automatically detect other kind and conditions of consumptions anomalies through specific rule-sets.

Figure 38 : Pilot 3b-ROM-02 – Benchmarking dashboard: building energy consumptions compared year by year; note the anomaly Gas metering for building n.1803 on 2021.

- **LLUC-3B-ROM-03 – Forecasting**

The Forecasting functionalities are periodically used by the officers of SIMU Department engaged in administrative tasks, including the Forecast Reports on expenditure.

Figure 39 : Pilot 3b-ROM-03 – Forecasting dashboard: whole asset energy consumptions for Gas (PDR) and for Power (POD) meters. First algorithm PROPHET.

The Covid restrictions impacted on the energy Consumptions depending on relevant reduction of most of the municipal buildings, so different algorithms were been developed, tested and then 2 of them implemented (Prophet and DeepAR) in order to take into account the anomalies in the time-series induced by covid emergency. The aggregation for Districts or for buildings Typologies is one of the main task the users are conducting in order to produce periodic reports. KPI_07 is also a measure of the benefit and frequency of use of functions within this service. An other KPI for this service related to the appreciation rating assigned by the users is the KPI-08.

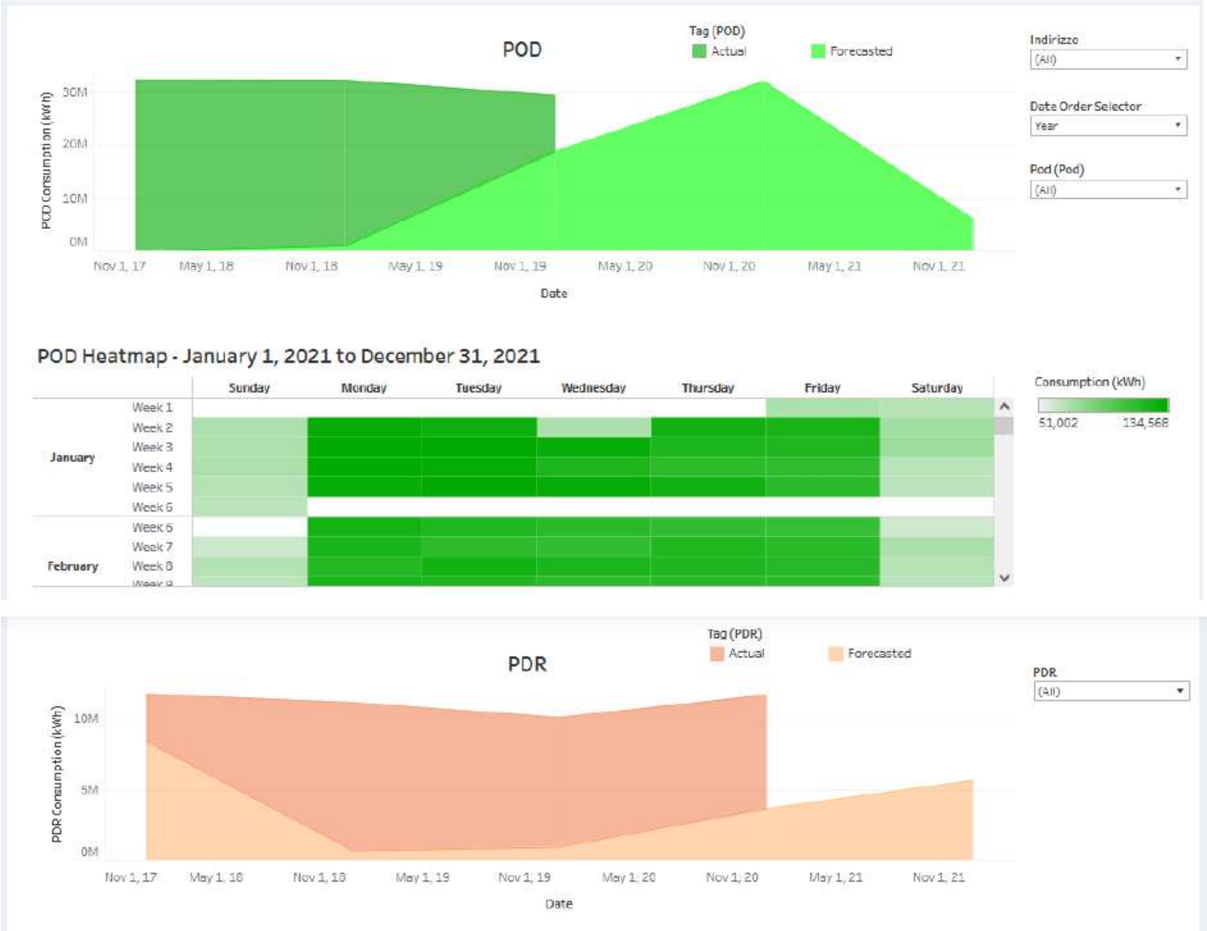


Figure 40 : Pilot 3b-ROM-03 – Forecasting dashboard: whole asset energy consumptions for Gas and for Power meters. Second algorithm DeepAR. A POD Heat map is also presented.

- **LLUC-3B-ROM-04 – RES Potentialities (PV plants on roofs)**
  This service is highly appreciated in the SIMU Department as it supports directly the planning process for PV plants asset extension on the owned buildings roofs. During the project the introduction at national level of new public incentives and connection schemes related to Renewable Energy Communities (REC scheme, Sharing PV energy surplus with other proximity users) prompted the pilot project team to redefine the scope and implementation of this service 3b-ROM_04 in order to obtain the estimation for each roof of the maximum peak power and the maximum PV production surplus (over the self-consumption quote of the building).

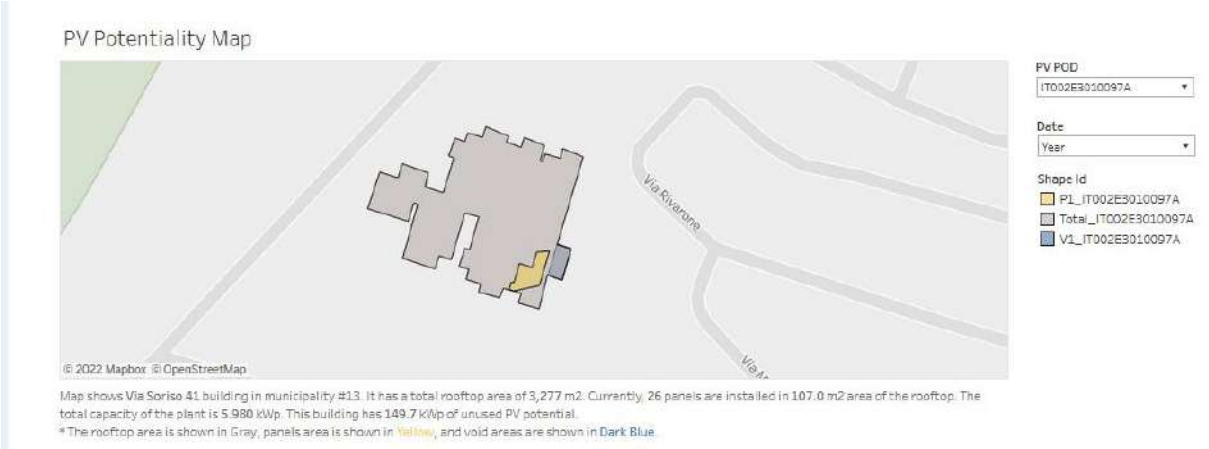


Figure 41 : Pilot 3b-ROM-04 – RES Potentialites dashboard: for each building hosting a PV plant the map shows and calculates the free surface useful to expand the PV plant.

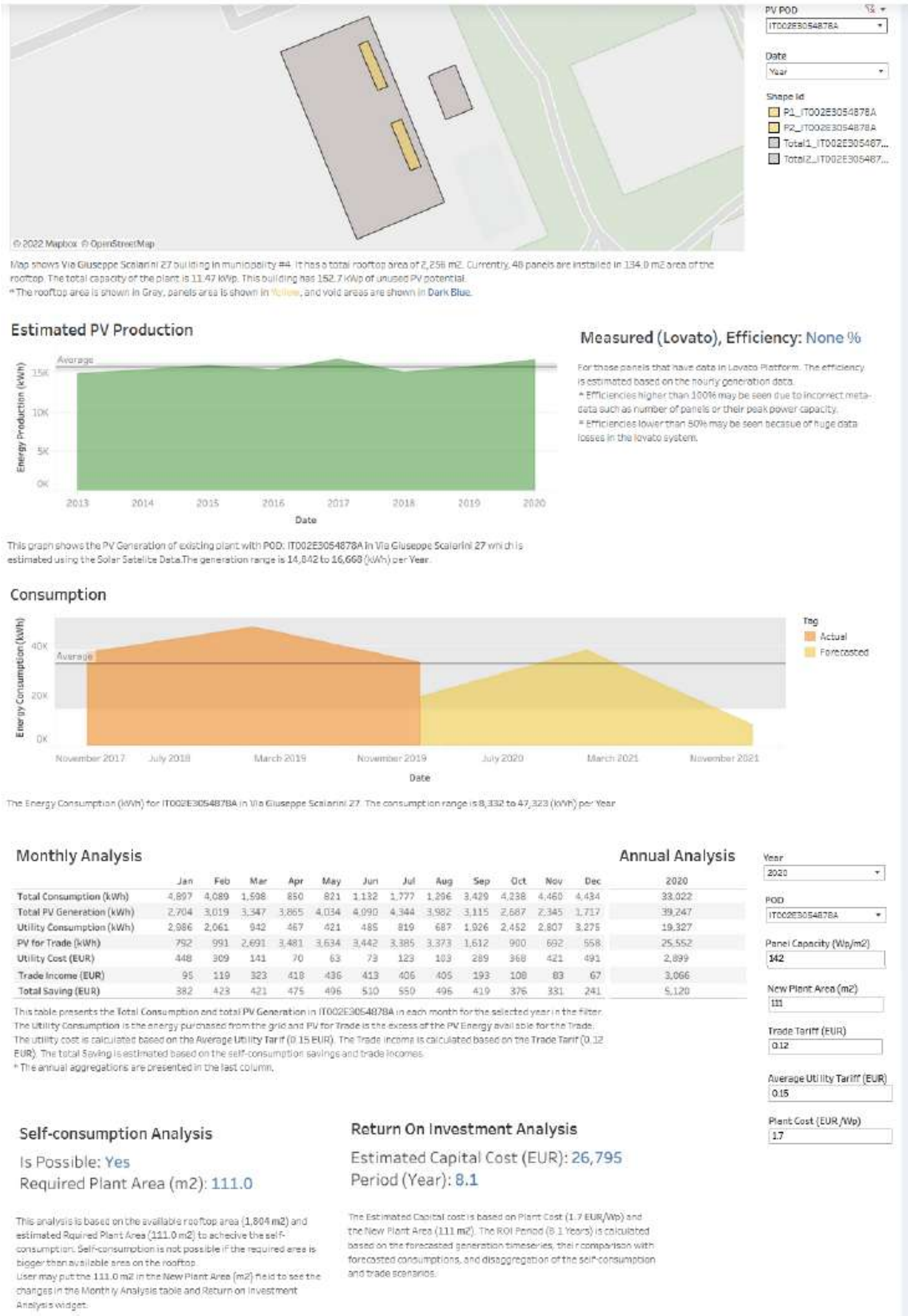
The KPI_06 (kWh/y of RES production that can be installed on the roofs) is now limited to the extension of 160 roofs already hosting an existing PV plants, where the algorithm calculates the free surface available, applying custom parameters for PV technology to simulate for the new PV plant, and gives as outputs the Total RES Production (kWh/y) that can be realized, the investment and the ROI.

The result is excellent (more than 1.200.000 kWh/y estimated from new PV plants) and can directly influence the planning strategy of the Municipality accelerating the design and the realization of many PV plants within the REC scheme.
The RES stakeholders, civil society organizations and the municipalities are going to meet and discuss in the next period to define the business model and the operative strategy for RECs on public roof, probably giving priority to school roofs, creating synergies also with an other EU funded H2020 project (SUN4ALL) involving the municipality since October 2021.

The services could be extended in the next future also to the roofs not already hosting any PV plant to calculate the new plant installation potentialities and also to estimate the costs and the CO2 impacts for these eventual future investments.

Automatic calculations can be improved introducing more accurate data on free surfaces and ideal orientation/tilt on the roofs.

The following figure shows the PV potentialities for each building roof where is possible to expand the PV plant, PV yearly production is estimated then the investment cost and the Pay-Back Time. The self-consumption is calculated and also some standard commercial features of the largest PV plant that seems feasible on that roof.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	2020
Total Consumption (kWh)	4,897	4,089	1,598	850	821	1,132	1,777	1,296	3,429	4,238	4,460	4,434	33,022
Total PV Generation (kWh)	2,704	3,019	3,347	3,865	4,034	4,090	4,344	3,982	3,115	2,687	2,345	1,717	39,247
Utility Consumption (kWh)	2,986	2,061	942	467	421	485	819	687	1,926	2,452	2,807	3,275	19,327
PV for Trade (kWh)	792	991	2,691	3,481	3,634	3,442	3,385	3,373	1,612	900	692	558	25,552
Utility Cost (EUR)	448	309	141	70	63	73	123	103	289	368	421	491	2,899
Trade Income (EUR)	95	119	323	418	436	413	406	405	193	108	83	67	3,066
Total Saving (EUR)	382	423	421	475	496	510	550	496	419	376	331	241	5,120

Figure 42 : Pilot 3b-ROM-04 – RES Potentialities dashboard

7.3 Conclusion

The evaluation of the pilot can be run at different levels : A. Energy Planning and Policy level; B. Information and Data Quality level; C. Energy Efficiency Technical level.
The consideration concerning the impact of the pilot on the Energy Planning and Policies (A) of Roma Capitale have to be updated once the Energy management organization of the municipality will be restructured (New Directorate on Climate) and once the CDP will be ready to host and publish Energy Data and will be connected with the Pilot Data. At present the impact that is verifiable and measurable is at the Energy Management Office level that benefit in terms of responsiveness, of completeness and depth of the cognitive picture, of full integration of the dashboard and the datasets on energy consumption and production (PV). In particular recently the PV potentialities service gained the attention of decision makers in the Municipality as the plan to design and realize Renewable Energy Communities – RECs – based on new PV plants on public roofs, is going to be discussed also in coherence with the Rome SECAP 2020-2030. Therefore the impact of Platoon Toolbox (Service 04) is resulting very relevant on the energy planning and policy level.

On the other hand, the Information & data quality level (B) evaluation is an ongoing process that focuses on the different data sources and on their evolution in time. The power and gas meters large asset analysed is evolving quickly grace to the installation of new generation meters, where the quality and frequency and accessibility of data is improved. At the same time the vendors and energy service providers change and can offer different data connectors (active connector to push data from their server) or web services (passive connectors to pull data from their communication services). Furthermore within WP7 the pilot has been enriched with near Real Time data coming from sensors (2400 assets for Heating and 15 Test sensors for Electricity mounted by the power meters) that are demonstrating a significantly increase in the Data quality, although this nRT and connectors sub-pilot has been completed on M35 so it is impossible to proceed with full user tests and energy analysis for these collected hi-frequency data flows.
The Energy Efficiency Technical Level (B) evaluation can be effectively conducted through most of the KPIs presented. This evaluation aims to describe and report the impact in terms of Energy Efficiency and End User experience (Officers of the SIMU department dealing with Energy management data and tasks) that the Pilot is producing or can produce in the next future, as during the first semester after M36 the end users will intensify their application on the toolbox. The complete results for all KPIs have been presented in par. 7.2

The KPI_01 (KWh/y saved already achieved 1.1 % of the total 87.000.000 kWh/y in power consumed) and the correlated KPI_05 (reduced CO2) together with KPI_02 (Personnel cost reduction) are the main indicators of the impact of the Pilot-3b-ROM toolbox in terms of energy transition and sustainability and more specifically in terms of improved behaviours of the personnel (SIMU Department – Plants Operative Unit) engaged in the energy management of the Rome Municipality asset.
The general idea is that each session or use of the Toolbox (KPI_07) can produce knowledge, information and indications on how to improve the energy efficiency of this large asset of buildings. This awareness can result directly or indirectly into actions. Direct actions on buildings plants, meters or management can be recorded in the notification area of the toolbox marking the date of each specific intervention and consenting to later calculate the reduction of the EC for the correlated meters. This means that only few types of direct actions consent to use the toolbox to quickly calculate the KPI_01 (i.e. dismission of meters) while the majority of the enabled interventions need a longer observation period to calculate the effective resulting savings. The toolbox services for forecasting can help to estimate the expected saving after one or two months from the intervention on the basis of the data flow frequency coming from the meters.

Indirect actions to improve energy efficiency consist in planned interventions or scheduled maintenance; in this case the KPI_01 validation will proceed with the recording of the scheduled intervention in the notification area and with the estimation of the future impact in terms of yearly saved energy.
KPI_08 focuses on the direct evaluation of the four services by the end users in the SIMU department, and even if the toolbox dashboard has to be considered a beta-release most of the users ratings are above the threshold, so sufficient, and the users comments and suggestions will help the evolution of the platform within the exploitation plan in order to match at the best their practical needs and the specific expectations.

8. Pilot 3C Evaluation & Validation Report

8.1 Introduction

Pilot 3c focuses CIC Nanogune building which is a public research center located in San Sebastian (SPAIN) managed by GIROA-VEOLIA. The building has 7319 m2 distributed over six floors and it contains offices, 15 ultra-sensitive laboratories and a cleanroom of nearly 300 m2 where the air purity is under strict supervision. The building has a BMS system and PV panels installed on the roof. Pilot 3c focuses on two main low-level use cases:

- LLUC-3C-01-Advanced EMS
- LLUC-3C-02-Predictive Maintenance

8.2 LLUC-3C-01-Advanced EMS

The objective of this use case is to match the demand prediction and RES generation prediction and to optimize the operation of building HVAC in order to achieve two objectives: (1) reduce the grid dependency and (2) reduce the energy bill.

8.2.1 Evaluation and Validation

Table 29: LLUC-3C-01- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1	Integration	1	0.8	IDS connector between TECN and GIR could not be implemented due to a conflict between Veolia's server structure and security protocols, which don't seem to allow the process to issue an SSL certificate required to pull data through the tunnel. Howeverver IDS connector was implemented between Barabara IoT and TECN as part of the open call in WP7.
2	Energy Bill reduction	20%	51%	Results seem promising. However, it must be highlightred that validation are
3	RES utilisation ratio	30% increase	7.5%	

				not fully representative as it has been validated with one week. Further validation would be needed with a longer time range.

The tools were trained with data from 01/07/2021 to 29/08/2021 and validated with wo weeks of data one for hot conditions (24/082021-31/08/2021) and one for cold conditions (14/11/2022-20/11/2022) showing good generalisation capacity.

The figures below show the validation results for the 16th November 2022:

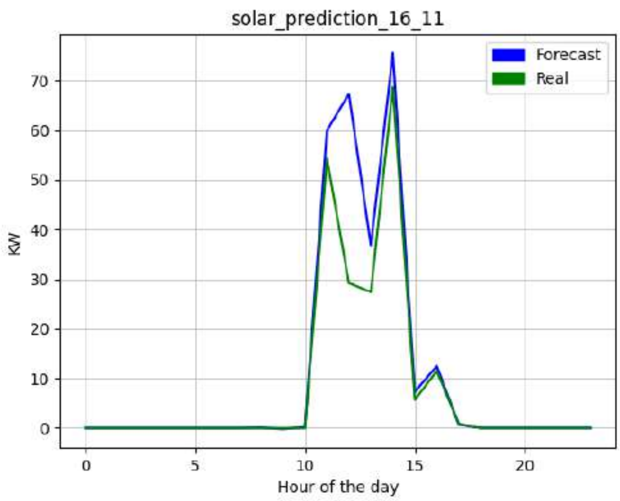


Figure 61: LLUC-3C-01-PV Forecaster – Predicted vs Real PV energy generation

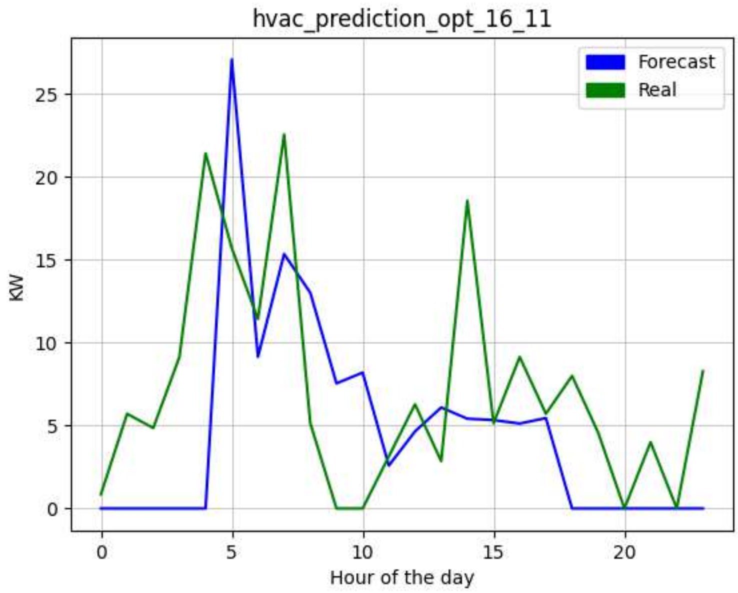


Figure 62: LLUC-3C-01- Energy Bill and RES Usage Optimiser – Optimised Forecast vs Real HVAC energy consumption

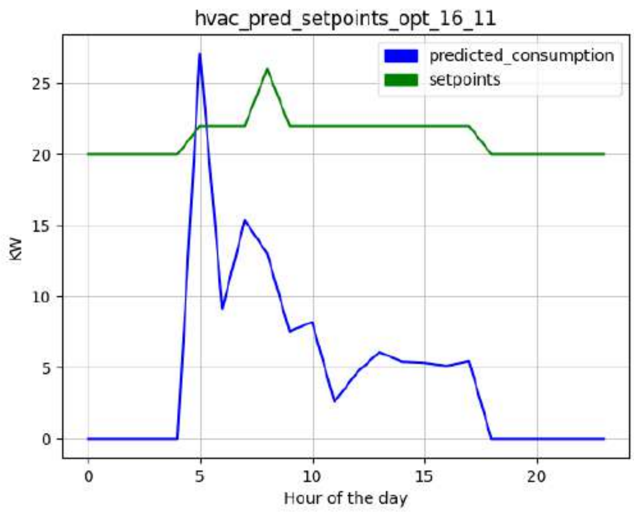


Figure 63: LLUC-3C-01- Energy Bill and RES Usage Optimiser – Optimised Forecast and Optimised Setpoints

The table below shows the validation results for the most recent validation data in November 2022:

Table 30- LLUC-3C-01-Validation data results

	Energy Bill HVAC - Actual (euros)	Energy Bill HVAC - After Optimisation (euros)	PV Self consumption Energy (kWh)	Overall energy consumption HVAC + Base (kWh)

14/11/2022	36	19	6	345
15/11/2022	22	9	8	263
16/11/2022	17	10	28	248
17/11/2022	25	5	29	353
18/11/2022	39	27	38	411
19/11/2022	28	11	30	456
20/11/2022	22	11	38	272
Total	**188**	**92**	**177**	**2348**

Results seem promising. However, it must be highlightred that validation are not fully representative as it has been validated with one week. In addition the validation is done in November where the HVAC consumptions is high and PV generation is low. Unfortunately, it could not be validated with more data due to some problems with GIR database persistence. The problems are solved now so further validation should be be completed with a longer time range to be able to get relevant conclusions.

8.3 LLUC-3C-02-Predictive Maintenance

The main objective of this use case is to have a centralised control of the health status of different equipment of the building HVAC system based on the readings from multiple sensors for each machine. Amongst all the machines that form the building HVAC system, this use case focuses on two types of machines:

1. Hydraulic Pumps
2. Chillers

8.3.1 Evaluation and Validation

8.3.1.1 Hydraulic Pumps

Table 31: LLUC-3C-02-Hydraulic Pumps-KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1	Health Monitoring	100%	100%	The developed algorithm is able to distinguish well the healthy and non-healthy operation using test data from an open-source dataset. Now we are validating with real data from GIR.
2	Failure Forecast	24 hours	~3 hours (170 mins)	The system is able to detect failure 3 hours in advance which is below the target value but should be enough time to be able to start the twin pump and avoid stopping the system.
3	Availability	N/A	N/A	This KPI cannot be applied in the case of pumps as there is no sufficient information to calculate it.

4	Mean Time Between Failures	N/A	N/A	This KPI cannot be applied in the case of pumps as there is no sufficient information to calculate it.
5	Maintenance Costs	N/A	N/A	This KPI cannot be applied in the case of pumps as there is no sufficient information to calculate it.
6	Integration	1	0.9	Implemented all the pipeline the using the Barbara OS except IDS part that not working due to issues with proxy and communications. Still pending integration with PLATOON edge-cloud framework.

In order to validate the data analytic tool for predictive maintenance of hydraulic pump different size of training datasets have been considered. For illustrative purposes the 100 vs 100 configuration has been represented. 100 vs 100 means that first 100 samples (files) have been used for training and last 100 samples (files) have been used to validate the outcomes. The expected result would release a failure scenario for no more that 10-15 final samples.

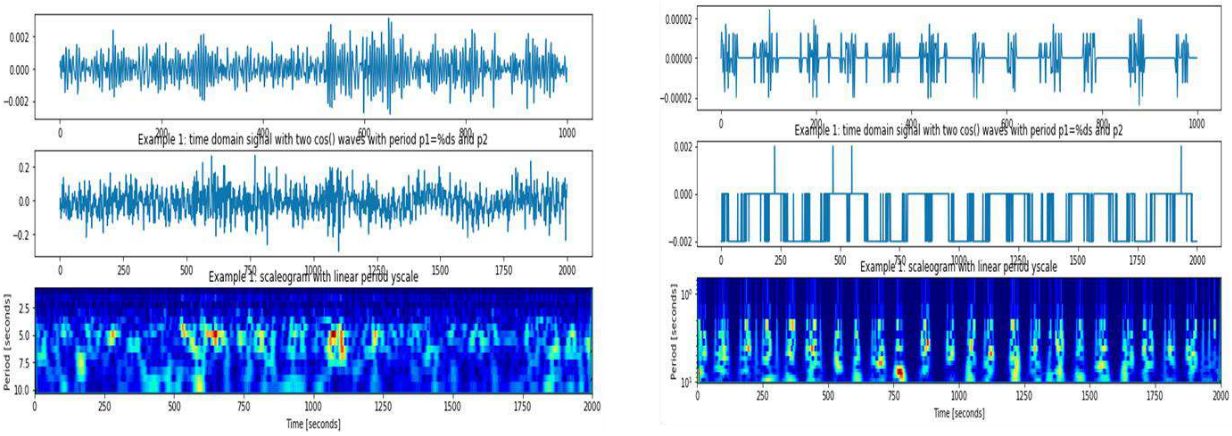


Figure 64: LLUC-3C-02-Hydraulic Pumps-Behavior for the first and final samples

Equally, different algorithms have been validated, namely a SVM OneClass Classifier, k-MEANS OneClass Classifier and DEEP AutoEncoder OneClass Classifier. Amongst all of them the one that produced the best results was the DEEP AutoEncoder OneClass Classifier. Equally, for each of the algorithms different hyperparameters have been attempted. The table below shows the validation results for different hyperparameter combination of the DEEP AutoEncoder OneClass Classifier.

The results shown below have been used to identify which was the optimal or at least the appropriate size for the training and testing datasets. It is important to mention that the anomaly detection algorithm is implemented as a streaming algorithm, so, inappropriate sizes of datasets could lead to identify all testing samples as anomalies or the other way around, to not detect any anomaly.

Table 32: LLUC-3C-02-Hydraulic Pumps-Results for different hyperparameter combination of the DEEP AutoEncoder OneClass Classifier

Modelo	DataSet	Train	Test	Anomalies Result
Relu – MSLE	100	90	10	from 10 to1
Relu – MSLE	200	190	10	from 10 to1
Relu – MSLE	300	290	10	from 9 to 1
Relu – MSLE	300	290	20	from 13 to1
Relu – MSLE	600	530	50	from 42 to 30
Relu – MSLE	600	600	50	from 17 to 3
Relu – MSLE	600	600	100	from 17 to 3

Analysing the results, delivered using the autoencoder approach with "ReLU" activation function and "MSLE" reconstruction metric provided it can be concluded that the optimal train and test dataset size are in the window of 500 to 600 samples from training and 50 to 100 samples for testing. Using values within that range the count of anomalies detected in the testing data was in worst case the 20%. Values above that 20% would mean too many samples classified as anomaly on the other side of the window, accept al samples as normal behaviour wouldn't be interesting either. In order to maximize the computational performance the tuple of 500 as train dataset size and 50 as test dataset size were selected

After selecting the appropriate size for the training and testing datasets, the FEMTO and IMS were tested with the implemented vibration PHM tool described in D4.10. The tests carried out released that only de AutoEncoder approach was reliable enough to implement a PHM tool free of "False Negatives", this means failures without previous notification.

The table below describes the outcomes for the two best scoring implementations, AutoEncoder and OC-SVM algorithms. The sample count in test count the amount of valid data reading to bearing failure. The change point and rest of columns indicate in which sample was detected the behavour change of the bearing and how much it supposes in real time to failure and percentage time to failure or the remaining useful life in each case.

Table 33: LLUC3C-02-Hydraulic Pumps- Validation Results – IMS and FEMTO

Test Id	Algorithm	Sample count in test	Change point sample	Time to Failure	Time to Failure (%)
IMS Test 1	Auto Encoder	2156	920	206 hours	57%
IMS Test 2	Auto Encoder	2156	1390	127 hours	35%
FEMTO Test 1	Auto Encoder	3269	1890	2hours 30 mins	32%
FEMTO Test 2	Auto Encoder	1015	826	7 minutes	4%
FEMTO Test 3	Auto Encoder	1802	1311	81 minutes	27%
IMS	OCSVM	2156	600	259 hours	72%

Test 1					
IMS Test 2	OCSVM	2156	None	Not Available	
FEMTO Test 1	OCSVM	3269	420	6 hours 40 mins	85%
FEMTO Test 2	OCSVM	1015	826	7 minutes	4%
FEMTO Test 3	OCSVM	1802	None	Not applicable	Not applicable

In order to evaluate the feasibility of the implementation the computational requirements were evaluated for most reliable approach ,AutoEncoder. The table below describes the average values for the AutoEncoder implementation:

Table 34:LLUC3C-02-Hydraulic Pumps- Average computational time for the AutoEncoder implementation

Model Size	First Train Time (average)	50 Samples Incremental Train (average)	50 samples evaluation Time (average)
IMS 500 samples	190.7 seconds	28.1 seconds	6.5 seconds
FEMTO 500 samples	90.7 seconds	8.1 seconds	6.5 seconds

With all the preliminary implementation and evaluation work described above the whole vibration PHM tool chains was moved to an edge framework deployment at NanoGUNE building. The results of a monitoring campaign of 8 months can be summarized as:

- Anomalies were detected in several stream data samples
- Aggregated anomalies time series did not deliver any behavioural change.
- The effective PHM tool chain described a healthy pump

The figure below shows the validation results for GIR pilot in CIC NanoGUNE in healthy operating conditions as described above:

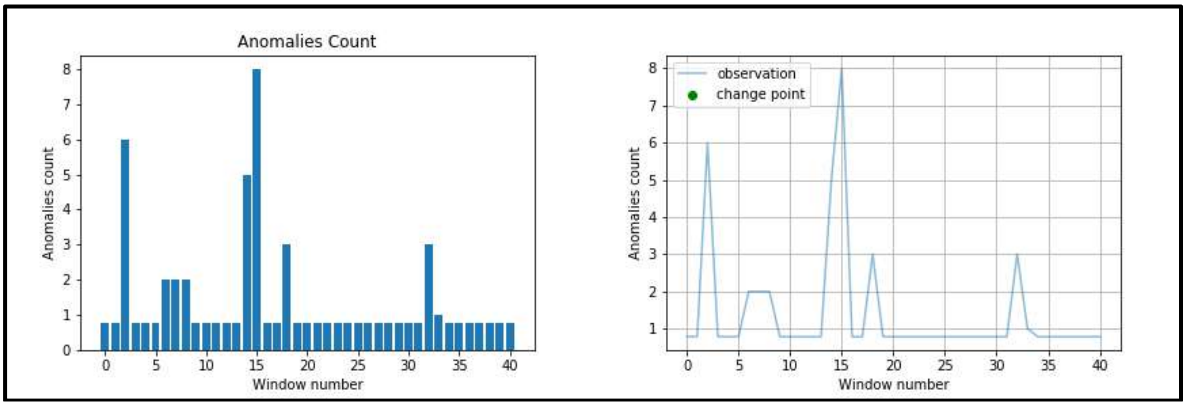


Figure 65: LLUC3C-02-Hydraulic Pumps- Validation Results – NanoGUNE

As a conclusion it can be noted that the current algorithm is looking into the symptom (vibration) rather than the cause (bearing crack due to fatigue). The bearing crack is a sudden phenomena, so, it is difficult to predict much in advance just looking into vibrations. Thus, in order to be able to predict failure in advance, we should look into the cause by using some type damage accumulation formula (e.g. Palmgren-Miner). However, this is a totally new approach that is out of the scope of the project but could be explored in a new project.

Regarding the integration KPI, all the pipeline has been validated using the Barbara OS and everything is working except the IDS part due to issues with proxy and communications. The corresponding evidence is included in the test report as part of Open Call deliverable part of WP7. Also, PLATOON edge-cloud framework has been implemented as an alternative to the Barbara OS system.

Finally, the data analytics tools have been validated with real data from GIROA. However, this has 2 main limitations: on the one hand, we have limited data as the sensors were recently installed. On the other hand, we don´t have failure data, so, we are just be able to test that the algorithm predict well in healthy operating conditions.

8.3.1.2 Chillers

Table 35: LLUC-3C-02-Chillers-KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1	Health Monitoring	0 – 100%	0 – 100%	This is an aggregated Health Status view of the machine, based on the Health Status of the different elements of the machine. It is based on a weighted average formula
1.1	Energy Variator	R^2 >= 0,85	R^2 = 0,92	Digital twin models show high accuracy with the real data. The system can detect whether a fault has occurred.
1.2	Evaporator Outlet Temp	R^2 >= 0, 85	R^2 = 0,92	Digital twin models show high accuracy with the real data. The system can detect whether a fault has occurred.
1.3	Flow Meter	MAE <= 2	MAE = 1,53	The high variability of this scenario requires different Scorer for the validation. Using a MAE verification below 2% we can distinguish a Bias of 1,8% (112m^3h vs 2$m^{3h)}$
1.4	Power Consumption Increase	R^2 >= 0, 85	R^2 = 0,96	Digital twin models show high accuracy with the real data. The system can detect whether a fault has occurred.
1.5	Temp Increase	R^2 >= 0, 85	R^2 = 0,915	Digital twin models show high accuracy with the real data. The system can detect whether a fault has occurred.
1.6	Phase Imbalance	Imbalance %	Imbalance %	Rule based indicator detects health status problem if the imbalance of the voltage of phases is over 3%
1.7	Power Supply	R^2 >= 0, 85	R^2 = 0,915	Digital twin models show high accuracy with the real data. The system can detect whether a fault has occurred.

1.8	Starter	MAE <= 2	MAE = 1,42	The high variability of this scenario requires different Scorer for the validation. Using a MAE verification below 2% we can distinguish a Bias of 1,8% (112m^{3}h vs 2m$^{3h)}$
2	Availability	0 – 100%	99.58%	Thanks to CMMS Integration, we are taking required information to generate and import availability KPI to the main dashboard
4	Mean Time Between Failures	Calculated KPI	272514 h	Thanks to CMMS Integration, we are taking required information to generate and import MTBF KPI to the main dashboard
5	Maintenance Costs	Calculated KPI	260 €	Thanks to CMMS Integration, we are taking required information to generate and import MTBF KPI to the main dashboard
6	Integration	1	n/a	For the Pilot 3C, the integration with IDS has been developed for the low-level use case LLUC-3C-02-Hydraulic Pumps. The IDS approach does not make sense with Promind because it will always be running as on-premise architecture.

The main KPIs to be validated and the ones with greater interest for the Giroa business are the ones related whit the Health Status of the chiller.
Each failure mode has been thought as a process. Having in mind the failure mode of the machine, an output signal has been selected to represent the output of the process. The same principle has been applied for the input signals, so the ones which are representative of the failure mode process has been selected as input.

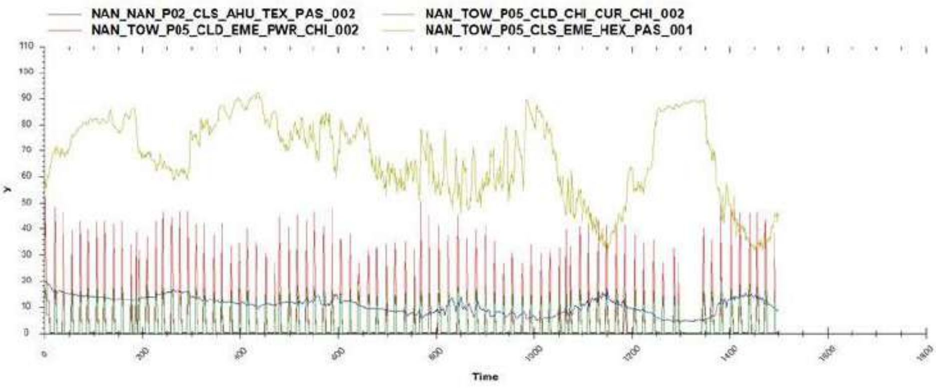


Figure 66: LLUC-3C-02-Chillers-input signals for Energy Variator model

Two ML approaches have been used to achieve best accuracy. Multilayer perceptron (MLP) and Random Forest models. After some benchmark testing the MLP model achieved the best accuracy. Hyperparametrization review has been performed with a result having the best performance with one hidden layer of 10 neurons, decay of 0,001 and learning rate of 0,01. The available real data has been split in 70% for training data and 30% for testing data.

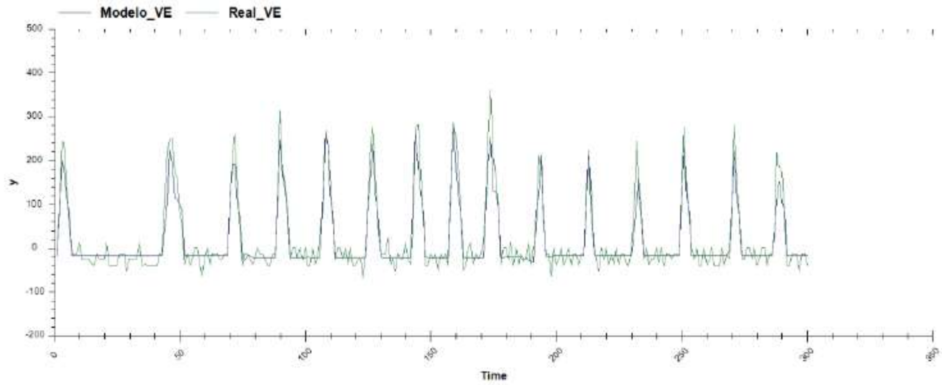


Figure 67: LLUC-3C-02-Chillers-Measured ThermicPower vs Predicted ThermicPower (Energy Variator Output)

All the KPIs are calculated and consolidated into a custom dashboard as shown in the figure below.

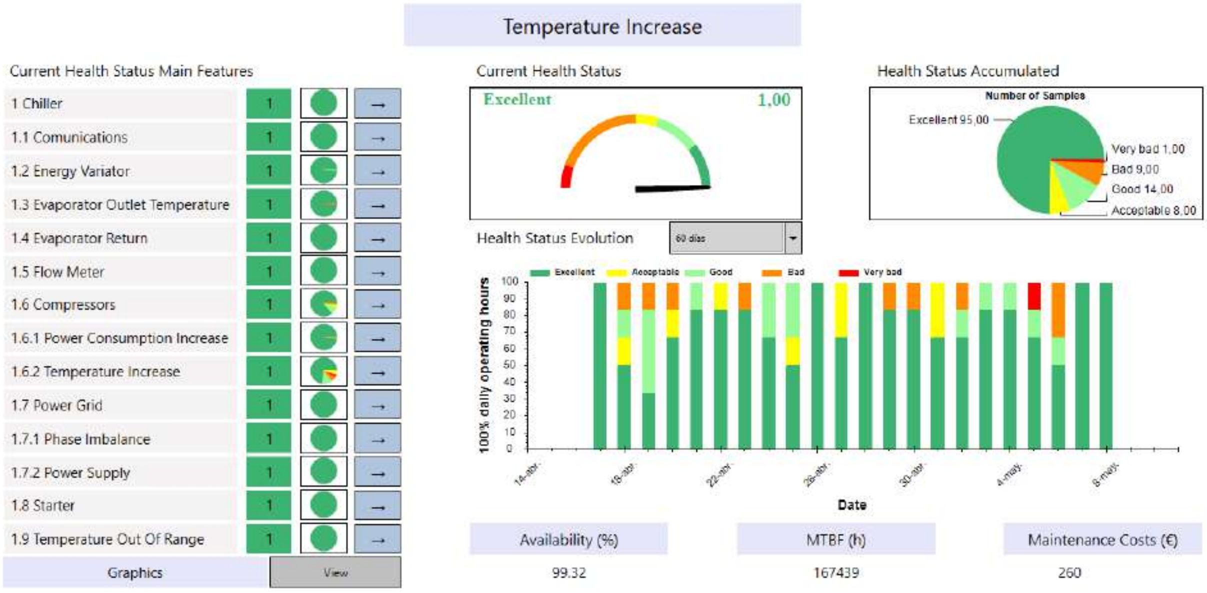


Figure 68: LLUC-3C-02-Chillers-Interactive dashboard for the hierarchical view of Health Status. Temperature Increase detail

8.4 Conclusion

As a result of the first validation it can be concluded that regarding Advanced EMS, the results seem promising specially regarding energy bill reduction showing a reduction of over 50%. However, it must be highlightred that validation is not fully representative as it has been validated with one week data due to some issues with GIR database. The problems are solved now so further validation should be be completed with a longer time range to be able to get relevant conclussions.

Regarding the predictive maintenance use case, it has been completed satisfactorily. On the one hand, the Hydraulic Pumps predictive maintenance tool has been validated with real operation pilot data from GIR and IMS and FEMTO data open data sources showing acceptable results in terms of health monitoring and failure detection. On the other hand, the results obtained from the Health Status analysis for the Chiller are of great interest. The system is able to determine whether the machine is working properly or if there is a malfunction problem not only at a machine level, but also identifying the machine-part or failure mode which is causing it.

9. Pilot 4A Evaluation & Validation Report

9.1 Introduction

This pilot takes place at the Multi-Good Microgrid Laboratory (MG2lab) in Politecnico di Milano, Italy. There is a single use case focused on Energy Management of Micro-grids (LLUC-4A-01) which aims to study data-driven energy management able to deal with increased complexity of the energy systems and to assess the advantages of innovative strategies: EMS with real-time processing and optimization for small-scale/renewable electricity generation, generation and load forecast, smart storage/generation.

9.2 LLUC-4A-01 Energy Management of Micro-grids

This use case focuses on data analytics tools aimed at the optimal exploitation of distributed renewable energy resources by means of an Energy Management Systems (EMS) with real-time processing and optimization for small-scale/renewable electricity generation, including specific implementation of day-ahead load consumption/generation forecast and nowcast capability. Indeed, the EMS is the algorithm that manages the forecasting modules for loads consumption and renewable energy production in view of the real-time management of all the energy assets in the micro-grid. The final aim is the optimization of unit commitment and scheduling of the energy resources on the base of these predicted profiles.

9.2.1 Evaluation and Validation

Table 36: : LLUC-4A-01- KPIs evaluation

KPI #	Description	Target Value	Actual Value	Comments
1	Energy availability	90%	>90%	Percentage of energy provided by renewable sources with respect to the measured consumption (the higher, the better).
2	Cost	10%	<10%	Reduction of efforts and costs in terms of percentage of energy from the electrical grid with respect to total energy consumption (the lower, the better).
3	Forecast Accuracy (%error)	20%	<20%	Accuracy of forecasting in terms of percentage error with respect to the daily

				measured energy (the lower, the better).
4	Realtime	80%	>80%	Ability of the system to monitor, forecast and optimize data in real time (the higher, the better).

In order to validate the data analytic tools for Energy Management of Microgrids developed in WP4, the different tools have been trained and tested with data from the MG2lab of Politecnico di Milano. A sample of the real-time collection of measurements of the MG2lab and the results of the implementation of this pilot specific tools is presented below, in Figure 69.

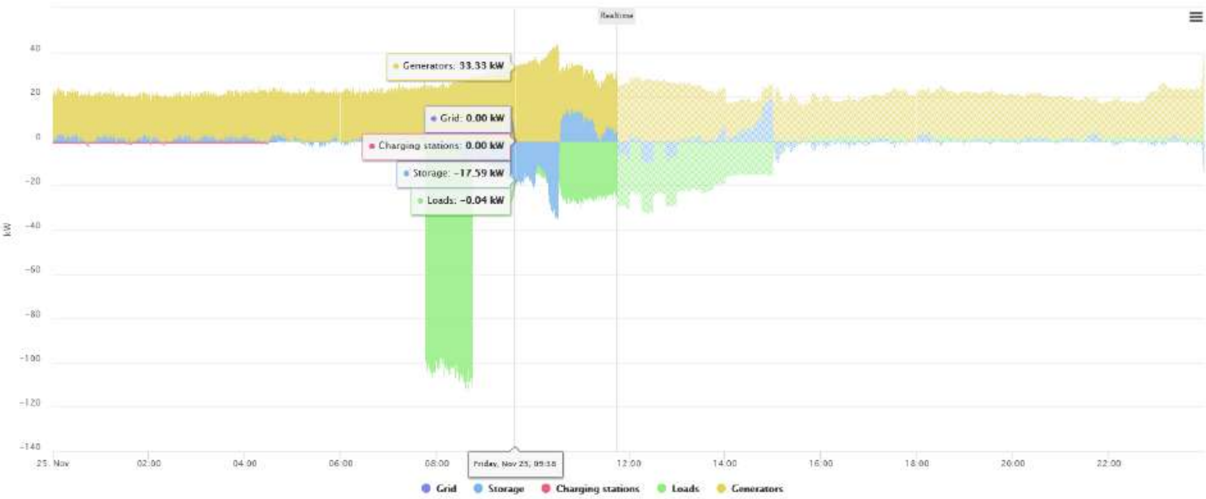


Figure 69: LLUC-4A-01-power production, storage and consumption of the microgrid in real time view.

To ensure the performance of the microgrid energy management, optimization and control, and to measure its efficiency, suitable key performance indicators have been defined to assess the meeting of the requirements and the targets defined for pilot 4a. In particular, 4 KPIs have been specifically defined, which have been finally evaluated on the last months of the project development; these validation tests were also important to provide feedback for improvement of the optimization of the energy management system.

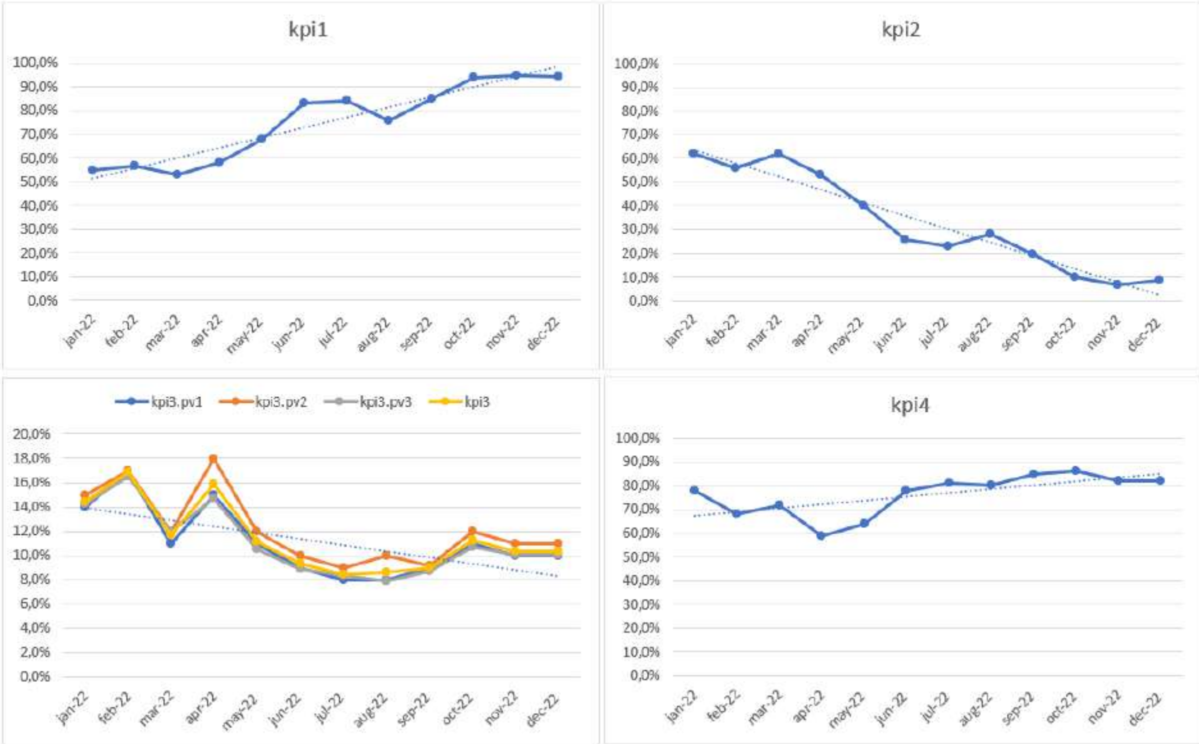


Figure 70: LLUC-4A-01-KPIs dashboard with a summary of the results of the relevant KPIS in the last part of the validation phase.

Regarding the KPI #1, related to energy availability, this indicator measures the percentage of energy provided by renewable sources with respect to the measured energy consumption, when the optimization for renewable electricity generation is performed considering smart storage and generation. In order to be able to evaluate this KPI, real power production ($P_{PV,t}$) and consumption ($P_{load,t}$) measurements are collected in real time at each considered time step from the micro-grid monitoring system, as described in the formula reported in the Annex I. The testing period spans across 24 hours, thus this KPI is computed with daily frequency by summing up the measured power values over the last 24 hours. The related results (in percentage) are reported into the consolidated dashboard (as shown in Figure 70). While higher percentage values correspond to a successful result in terms of energy availability, with an ideal target of 100% for this indicator, a threshold of 90% can be considered satisfactory.

Regarding the KPI #2, related to costs, this indicator measures the reduction of maintenance effort and costs in terms of percentage of energy from the electrical grid with respect to the total energy consumption, when the optimization for renewable electricity generation is performed considering smart storage and generation.
In order to be able to evaluate this KPI, real power production ($P_{PV,t}$) and consumption ($P_{load,t}$) measurements are needed, as described in the formula reported in Annex I. These measurements are stored within PLATOON platform data storage, obtained in real time at each considered time step from the micro-grid monitoring system and the related results (in percentage) displayed into the consolidated dashboard. The minimum testing period is over 24 hours, but additional time horizons can be considered to provide an additional report on the performance of the system, thus this KPI is

to be computed with daily frequency by summing up the measured power values listed above over the last 24 hours, but results will be also aggregated to longer time ranges with the increasing of collected data.

While lower percentage values correspond to a successful result, with an ideal target of 0% for this indicator, a threshold of 10% can be set as a satisfactory target in terms of energy cost.

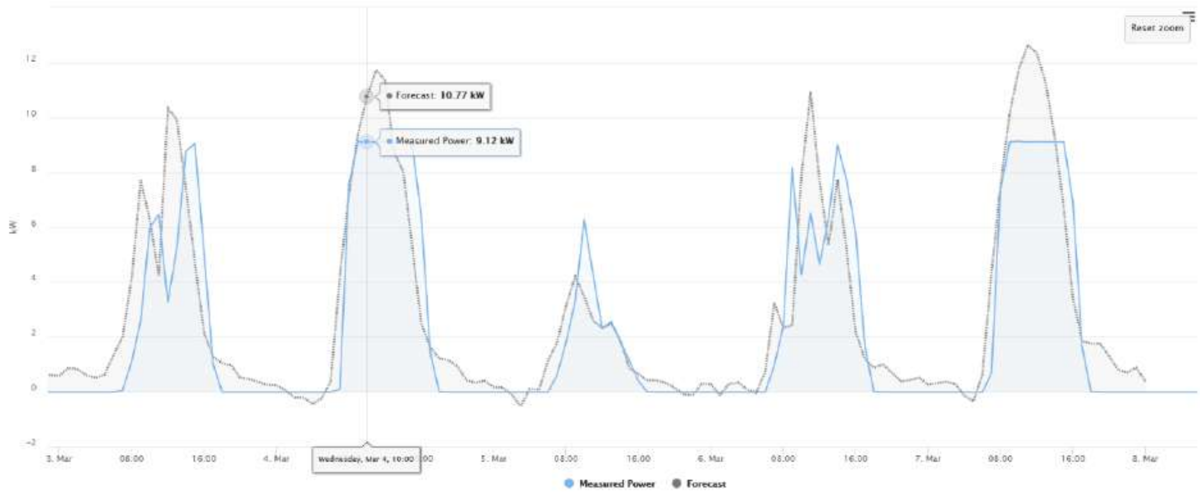


Figure 71: LLUC-4A-01-renewable power production and related forecasting.

Regarding the KPI #3, related to forecast accuracy, this indicator measures the accuracy of forecasting in terms of percentage error with respect to the daily measured energy, both for production and consumption, in particular considering the well-known normalized Root Mean Square Error indicator (nRMSE) and the recently introduced Envelope Mean Absolute Error indicator (EMAE), as described in the formula reported in Annex I.

In particular, this KPI is computed considering the daily power forecast with respect to its daily measurement, as reported in Figure 71. In order to be able to evaluate this KPI, power forecast ($P_{f,t}$) and real measurements ($P_{m,t}$) are collected and stored within PLATOON platform data storage, obtained in real time at each considered time step from the micro-grid monitoring system. The testing period is over 24 hours, thus this KPI is computed with daily frequency, by summing up the power values over the last 24 hours, and the related results (in percentage) displayed into the consolidated dashboard.

While lower percentage values correspond to a successful result in terms of forecasting accuracy, with an ideal target of 0% for this indicator, a threshold of 20% can be considered satisfactory for this forecasting accuracy.

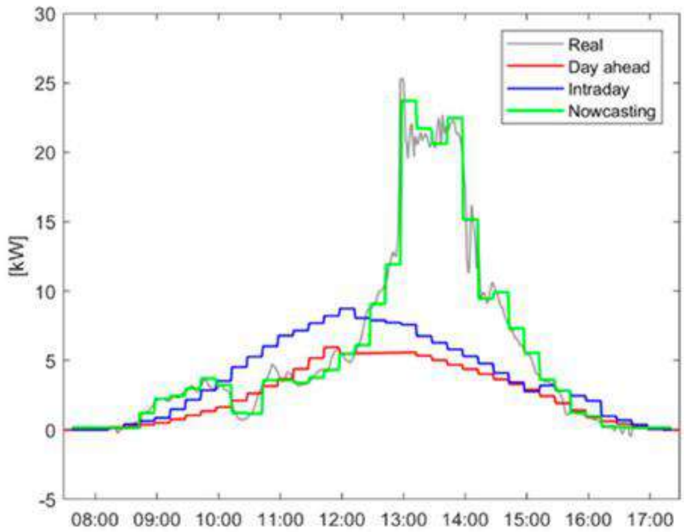


Figure 72: LLUC-4A-01-real time power forecasting adjustments by means of nowcasting technique.

Regarding the KPI #4, related to realtime capability, this indicator measures the ability of the system to monitor, analyse and optimize forecasting results at real time rate, when the prediction for renewable electricity generation is performed considering current weather conditions. In particular, the KPI related to realtime capability is measured considering the forecast skill of the nowcasting feature with respect to day-ahead forecasts, according to the formula reported in Annex I.
In order to be able to evaluate this KPI, the day-ahead power forecast ($P_{f,t}$) the most updated nowcast values ($P_{n,t}$) and the corresponding real measurements ($P_{m,t}$) are needed, as shown in Figure 72. These data and measurements are stored within PLATOON platform data storage, obtained in real time at each considered time step from the micro-grid monitoring system. The testing range spans across the last 24 hours, thus this KPI is computed with daily frequency and the related results (in percentage) displayed into the consolidated dashboard.
While higher percentage values will correspond to a successful result, with an ideal target of 100% for this indicator, a threshold of 80% can be set as a satisfactory target in terms of realtime capability of nowcasting.

9.3 Conclusion

As a conclusion of the exploitation and validation phase, it can be drawn that the implemented energy management system (EMS) for the experimental microgrid of Politecnico di Milano was able to reach the target KPIs regarding the renewable energy generation management and forecasting capabilities, thanks to the implemented robust optimization approach, based on the developed forecasting techniques.
The display of all the results in a consolidated dashboard (as shown in Figure 70) allows to visualize the KPI aggregation on different time horizons in order to appreciate the progress made during the last phase of the project. KPIs values appear to be aligned with the target defined at the beginning of the validation phase (and reported in Table 36), although some of them could be reached only towards the end of the project, in the last validation phase.
As a consequence of the presented results it can be concluded that the use case related to Energy Management of Micro-grids been completed satisfactorily.
The implemented real-time data collection allows to keep continuously updated the KPIs in order to maintain their consistency with the threshold values and the overall system target performance.

10. PLATOON Common Components Evaluation & Validation Report

10.1 Introduction

This section covers the validation results of the cross-pilot PLATOON common components.

10.2 Marketplace - IDS Metadata Registry (Broker/Appstore), Clearing House, DAPS and Vocabulary Provider

The PLATOON Marketplace is one common endpoint to access the data and energy services provided by all pilots. PLATOON Marketplace comprehends the following IDS components:

- Metadata Registry
- Graphical User Interface (GUI)
- Clearing House
- Dynamic Attribute Provisioning Service (DAPS)
- Vocabulary Provider

10.2.1 Evaluation and Validation

KPI #	Description	Target Value	Actual Value	Comments
1	Metadata Registry Integration	1	0.8	Metadata Registry has been successfully integrated with IDS DAPS and Connectors. The AppMessageHandler has been tested with DSC which was modified to perform the validation. The installation of the App through Connector is still an on going process and will be finished by M36.
2	GUI Integration	1	0.9	GUI was successfully developed for the Marketplace. Some pilot partners have tested and interacted with the UI.
3	Clearing House Integration	1	0.6	A new instance of Clearing House based on the latest release by Fraunhofer AISEC has been successfully deployed in the marketplace. The communication with the Clearing House has been tested with the TRUE Connector.
4	DAPS Integration	1	1	DAPS has been successfully integrated in the Clearing House and Metadata registry.

				All components interacting with the marketplace are authenticated through DAPS.
5	Vocabulary Provider Integration	1	0.8	Vocabulary Provider has been successfully integrated with IDS DAPS and Connectors. Integration with PLATOON datamodels is still pending as they have not been uploaded yet to a repository.

The PLATOON Metadata Registry has been successfully integrated with the TRUE Connector. As Figure 73 shows, the locally installed connector is running at https://localhost:8084 and the Metadata registry is running at https://localhost:8080. The "Forward-To" in the header of the message contains the URL of the Metadata Registry. The "ids:MessageProcessedNotificationMessage" shows that the local connector is successfully registered in the Metadata Registry.

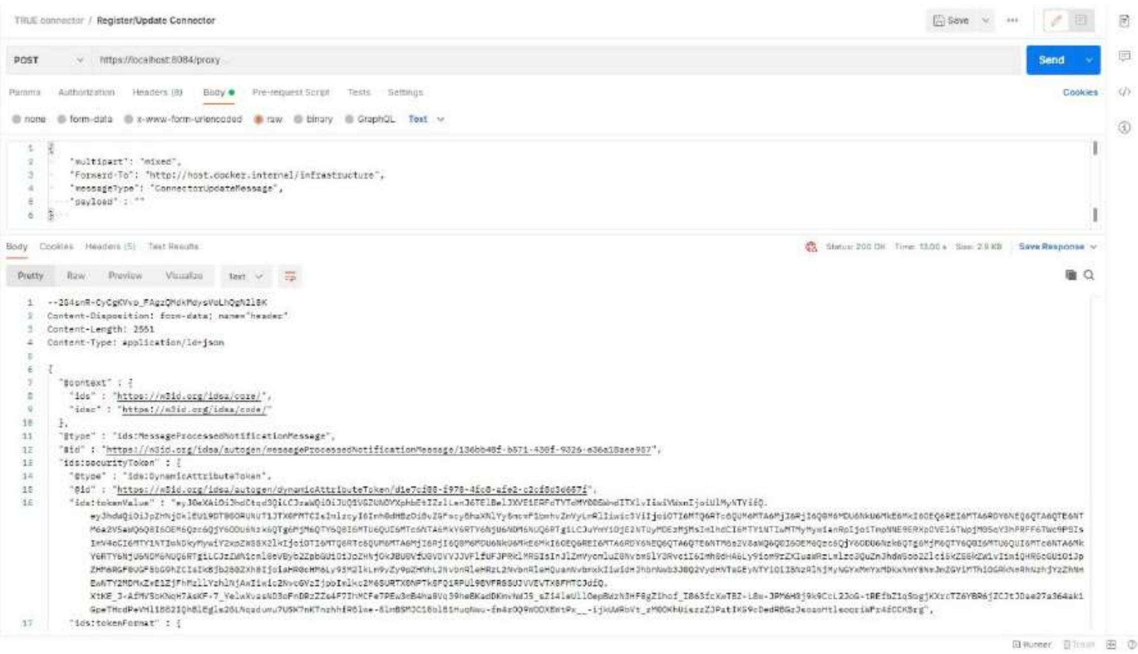


Figure 73:PLATOON Common Components - Integration of TRUE connector into the Metadata Registry

All the IDS components are authenticated through the DAPS. Figure 74 shows that when the upcoming Token from the connector is not Valid, Metadata Registry sends "ids:RejectionMessage" with the "Error verifying token".

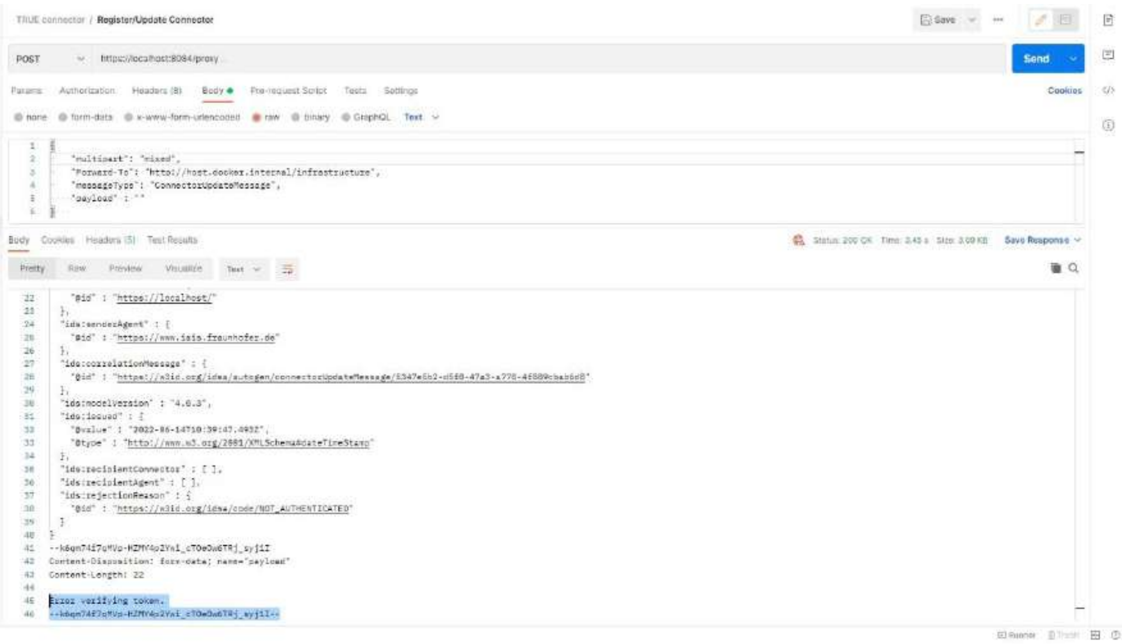


Figure 74: PLATOON Common Components - Integration of DAPS into the Metadata Registry

A GUI specific for PLATOON Marketplace has been developed and integrated into the Metadata Registry. The User Interface contains a Dashboard that shows the summary of all the registered Connectors, Resources, and Apps (services) in the Metadata Registry as shown in Figure 75. The **Datasets** and **Apps** windows shows the list of all the Resources present in the UI. If one clicks on any a dataset or an app, the window will show the details of it as shown in Figure 76.

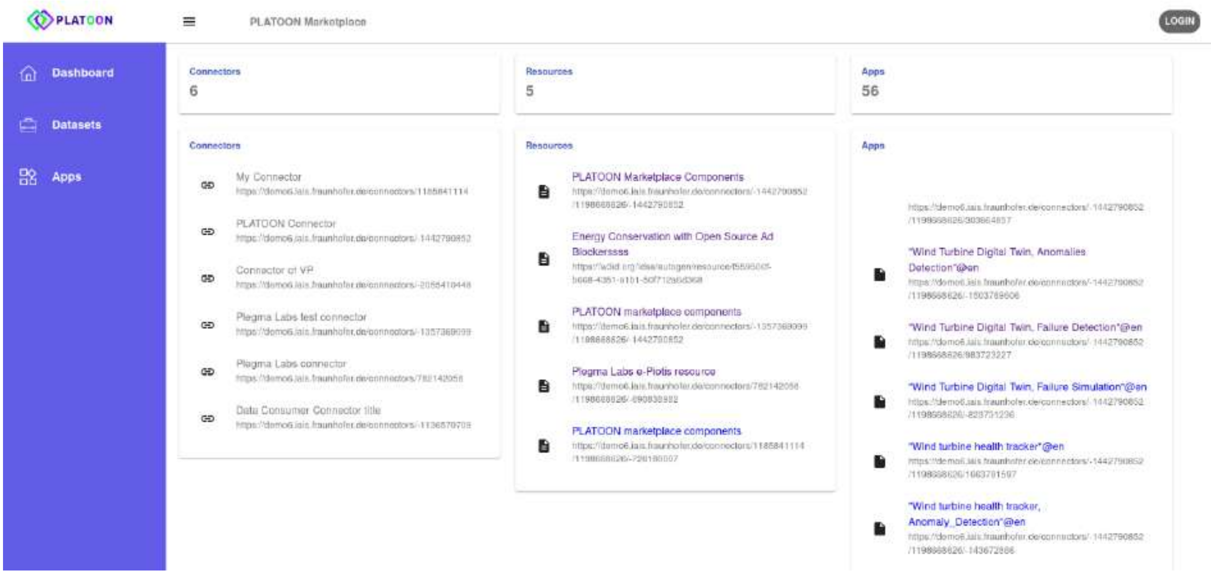


Figure 75: PLATOON Common Components - UI Dashboard

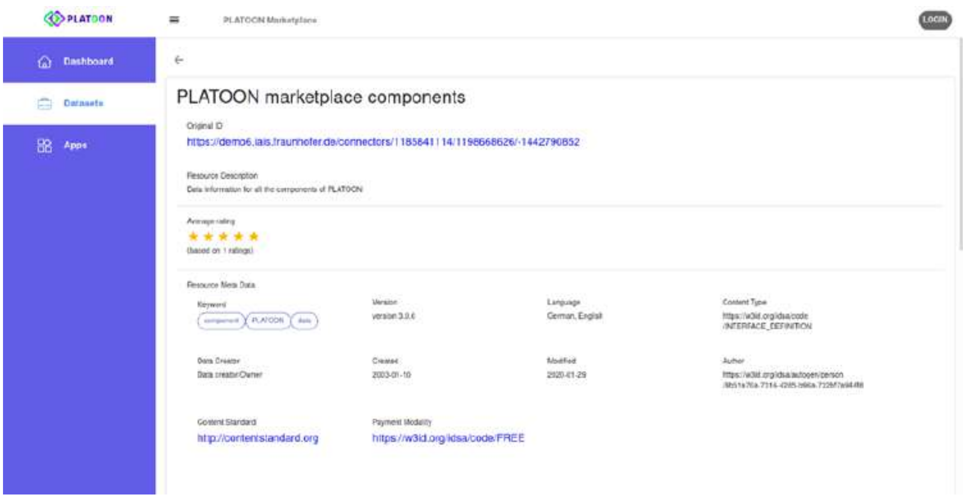


Figure 76: PLATOON Common Components - Dataset Window of the UI

The Data Space Connector has been modified so that user can insert their metadata from the Data Analytic Toolbox as shown in the image below:

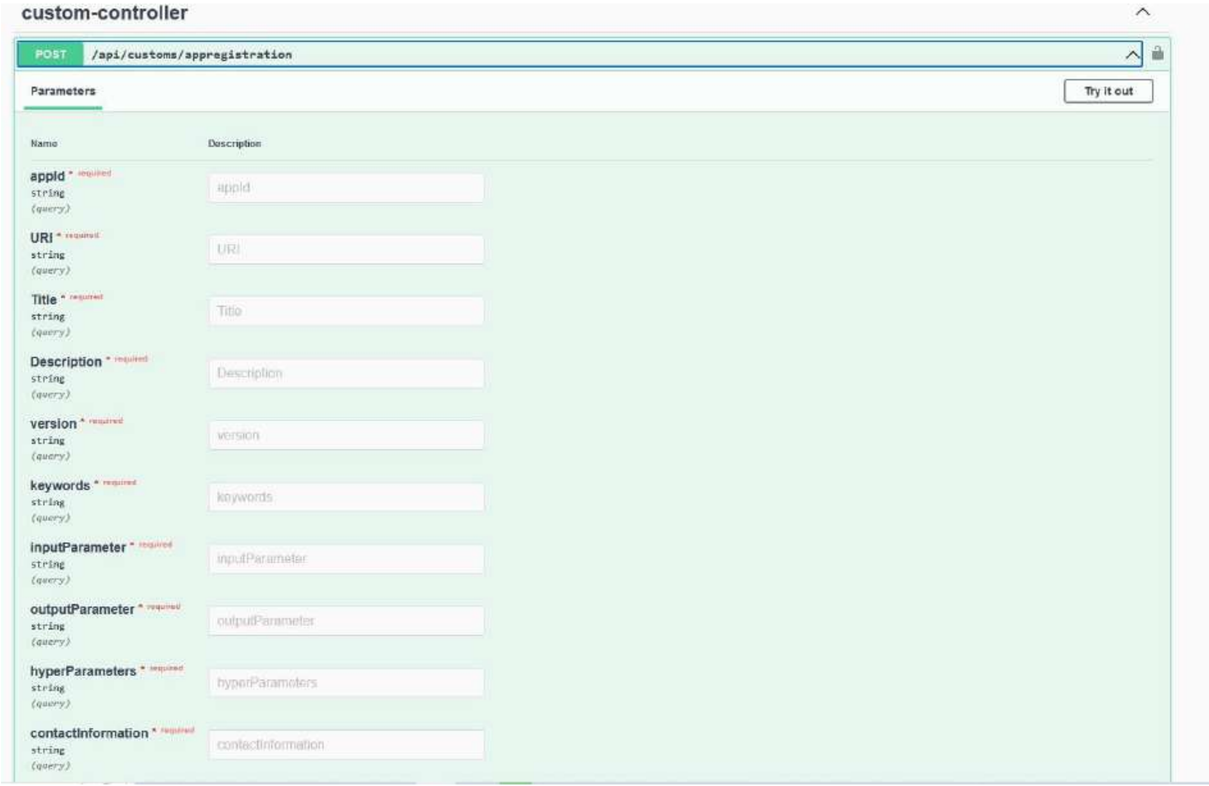


Figure 77: UI to register App from Data Analytic Toolbox through DSC

The modified DSC also allows users to unregister their App from the Metadata Registry as shown in the image below:

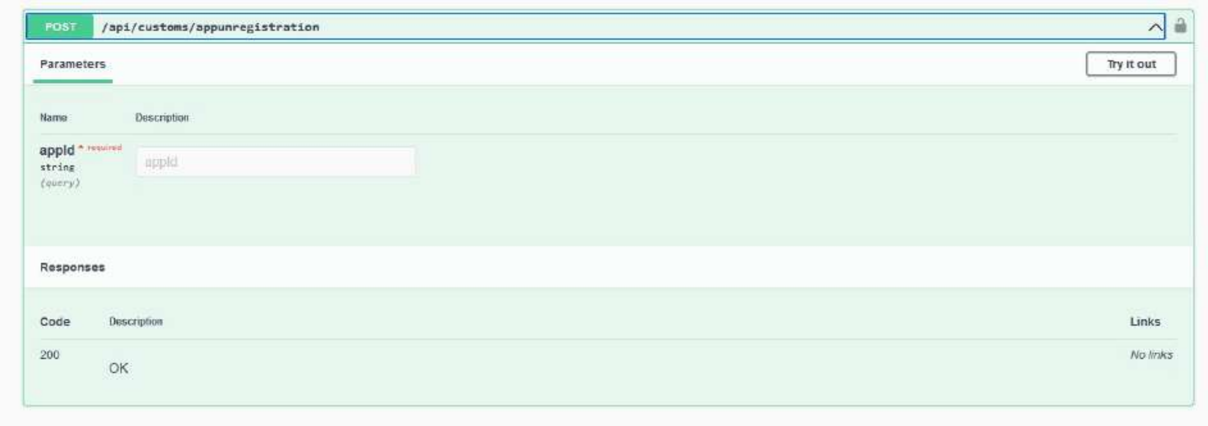


Figure 78: UI of DSC to unregister an App

Besides, the newest IDS Clearing House has been deployed for PLATOON. This component successfully integrates the DAPS. Without a proper Dynamic Attribute Token (DAT) coming from the DAPS, the Clearing House will not log anything and through a rejection message as shown in Figure 79.

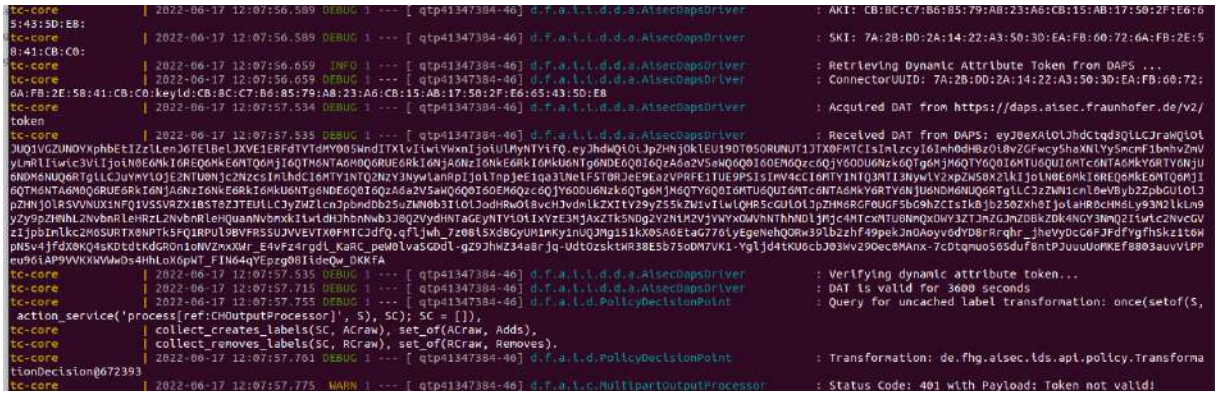


Figure 79: PLATOON Common Components - Rejection log from the Clearing House when token is not valid

With a proper token with the integration of a Connector, the Clearing House responds with a successful message as an example shown in Figure 80.

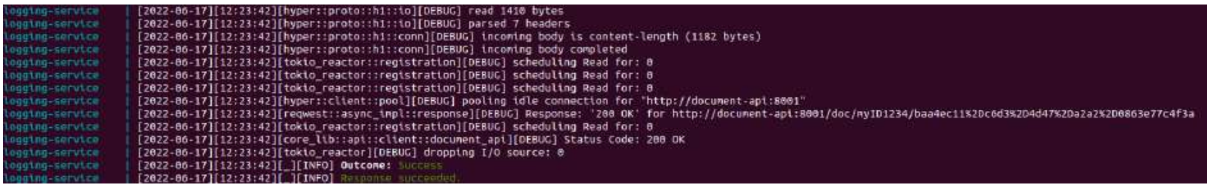


Figure 80: PLATOON Common Components – Successful response message from the Clearing House with respect to the Connector's incoming message

Finally, the PLATOON IDS Vocabulary provider has been successfully integrated with the IDS DAPS as it is able to manage the tokens generated. Equally it has been successfully integrated with the IDS connectors and can receive several IDS messages according to the IDS information model. The figure below shows the response of a query message that allows to interrogate a specific ontology directly from an IDS connector.

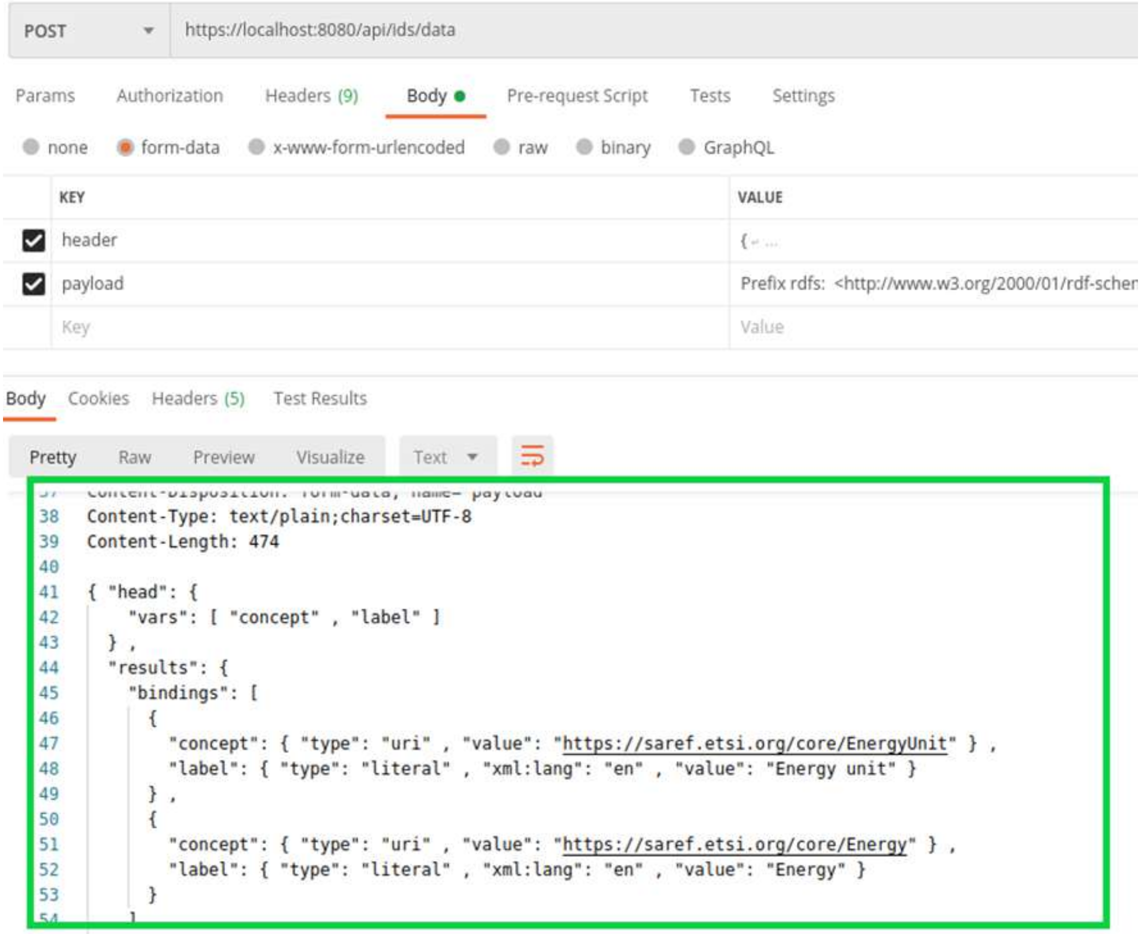


Figure 81: PLATOON Common Components - IDS Vocabulary Provider Validation Results

However, the integration of the PLATOON IDS vocabulary provider with the PLATOON data models is still pending as they have not been uploaded yet to a repository. ENGIE has bought a domain name, which we are currently deploying on the ENGIE´s side with the different security parts. More details on PLATOON Common Data Models are explained in deliverable D8.5.

10.3 Conclusion

As a result of the validation of the PLATOON Common Components it can be concluded that most functionalities of the Metadata Registry, Clearing House, GUI, DAPS and Vocabulary provider have been successfully validated. To validate the mechanism of the AppMessageHandler of the Metadata Registry, the Data Space Connector has been modified so that user can register their Apps from the Data Analytic Toolbox. The validation of the App Store is in-progress and will be completed by M36. The new version of the Clearing House can also communicate with the TRUE Connector. Regarding the PLATOON IDS Vocabulary provider, the integration with the PLATOON data models is still pending. ENGIE has bought a domain name, which we are currently deploying on the ENGIE´s side with the different security parts, so, this should be completed before the end of the project.

11. Conclusion

As a result of the final validation performed in the different pilots and the PLATOON common components, it can be concluded that most of the functionalities have been successfully validated , except some minor pending aspects as shown in the table below:

Table 37: Overall Validation Status Summary

Pilot	Status	Pending Aspects
1A	Complete	
2A	Complete	
2B	Complete	
3A	Minor pending aspects	Some tools could not be validated.
3B-PI	Complete	
3B-ROM	Complete	
3C	Complete	
4A	Complete	
Common Components	Minor pending aspects	• Metadata registry- Test the functionality of AppMessageHandler. • Vocabulary provider - integration with the PLATOON Common Semantic Data Models for energy.

In addition, it was noted that in general, the pilots faced two main barriers to complete the validation:

1. Implementation of IDS connector and semantic pipeline.
2. Lack of sufficient quality data for validation.

As lessons for future projects, on the one hand, the IDS connectors should be improved to facilitate the configuration processes so that even non-experts can configure them. On the other hand, it should be noted that due to the COVID situation, there have been some delays in the installation of the new sensors/systems. Nevertheless, if it had been possible for the pilots to have all the sensors and data at the beginning of the key phases of the project, this type of problem could have been avoided during the execution.

Annex I: KPI Templates

Pilot 1a Predictive Maintenance of Wind Farms

KPI N°1				
KPI-Name	Modelling quality		**KPI-ID**	1
KPI-Type	Technical (specific to the pilot use case) or business (refer to D8.1/ PLATOON KPIs) Technical			
Description	Accuracy of the predicted value compared to real value in healthy operating conditions using the Mean Absolute Percentage Error (MAPE).			
Target Value	Target value: 3%	Threshold Value 5%	The value used to assess the effectiveness/efficiency performance of the monitored process. RMS error	
Rounding	Round to 1%			
Unit	Percentage error			
Formula	(Abs(predicted value of modelled parameter – true value)/true value) * 100			
Calculating frequency	Upon retraining of the model			
Calculation Methodology				
Step	**Description**			
01-	Predict the value of modelled parameter			
02	Compare to the real value according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Signals used as input for the models	SCADA data	10 min	Data corresponding to training range for the model.	ENGIE

KPI N°2				
KPI-Name	Integration		**KPI-ID**	2
KPI-Type	Technical			
Description	Metric targeted at the validation of the fact that the tools of this pilot are able to work together.			
Target Value	1	**Threshold Value**	1	
Rounding	Not applicable			
Unit	Binary 1 or 0			
Formula	If all tools to complete the pilot data analysis can interact and send data to each other than this KPI is 1. Otherwise, it is 0.			
Calculating frequency	At each pipeline release			
Calculation Methodology				
Step	**Description**			
01-	based on unit tests the input-output functioning of each pipeline is validated.			
02	Test data is exchanged between the pilot analytics blocks			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Test data	Predefined set of validation data.			Each pilot party involved with specific tools

KPI N°3				
KPI-Name	Fault detection		**KPI-ID**	3
KPI-Type	Technical			
Description	Anomaly detection speed + accuracy (false vs true positive). The accuracy is expressed using a confusion matrix. For the speed this is expressed in time to catastrophic failure.			
Target Value	Compared to the current failure detection the speed should improve with at least 25%, while keeping false positives below 10%	**Threshold Value**	All improvement compared to current situation is already useful.	

Rounding	Not applicable for accuracy. Each element in the confusion matrix is binary. For the speed rounded to the next day.			
Unit	time			
Formula	Confusion matrix for each day block in time			
Calculating frequency	Once per day			
Calculation Methodology				
Step	**Description**			
01-				
02				
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
E.G. energy consumption	E.g. BMS	E.g. 15 min	E.g. Monthly	

KPI N°4			
KPI-Name	Processing capability	**KPI-ID**	4
KPI-Type	Technical		
Description	There are two aspects being tested in this KPI. The first is the speed at which one complete data analysis of the complete pipeline can be done. The second is the number of turbines that are feasible to be analysed using the approach.		
Target Value	Full processing chain for a farm should be able to run on a standard server.	**Threshold Value**	Full processing chain for a farm should be able to run on a standard server.
Rounding	Rounding up of CPU and RAM to next unit		
Unit	Nbr of s on CPU of type X with X Gb RAM for 1 turbine		
Formula	Cores and Gb		
Calculating frequency	Upon changes in the pipelines		
Calculation Methodology			
Step	**Description**		

01-				
02				
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Input data sources for the analytics methods	Input data sources for the analytics methods	Same as inputs for the analytics methods		

KPI N°5			
KPI-Name	Maintenance costs reduction	**KPI-ID**	5
KPI-Type	Business		
Description	The reduction in the maintenance cost of the wind turbine due to early fault detection. Less consequent damages are present and maintenance actions are clustered. Costs will be estimated by comparing cost of component replacement at detection to catastrophic failure. Revenues during additional time that the machine was able to run are subtracted from the maintenance costs.		
Target Value	10-20%	**Threshold Value**	10%
Rounding	Round to 0.01%		
Unit	%		
Formula	Euro maintenance cost with early detection/Euro maintenance cost run to failure		
Calculating frequency	yearly		
Calculation Methodology			
Step	**Description**		
01-			
02			

Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner

Maintenance records containing the maintenance actions performed on the wind turbines under investigation	Maintenance records	continuously	yearly	ENGIE

KPI N°6			
KPI-Name	Availability increase	**KPI-ID**	6
KPI-Type	**Technical (specific to the pilot use case) or business (refer to D8.1/ PLATOON KPIs)**		
Description	The increase of the turbine availability due to faster actions triggered by better predictive maintenance. We focus on machines with an error.		
Target Value	2-5%	**Threshold Value**	2%
Rounding	Round to 0.01%		
Unit	% of the time		
Formula	Abs(Availability as is situation – Availability after usage of Platoon toolbox)		
Calculating frequency	yearly		
Calculation Methodology			
Step	**Description**		
01-	Isolation of the availability reductions linked to the subcomponents within focus in Platoon.		
02	Comparison of the estimated availability with and without the fault detection knowledge of platoon analytics tools.		

Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Annotated stops	Maintenance records	continuously	yearly	ENGIE

Pilot 2a Electricity Balance and Predictive Maintenance

LLUC P 2a-03

KPI N°1a				
KPI-Name	Load Forecasting Mean Absolute Error		**KPI-ID**	LLUC 2a-03 KPI 1a
Description	This KPI is supposed to provide precision performance estimation for Load Forecasting models.			
Unit	[W]			
Formula	$$=\frac{1}{n}\sum_{i=1}^{n}\lvert e_i\rvert$$ where e_i is difference between estimated and real load and n is number of samples for which KPI is calculated.			
Calculating frequency	This KPI should be evaluated daily or monthly			
Calculation Methodology				
Step	**Description**			
01-	Estimated and real load from the PLATOON platform should be obtained and KPI should be calculated according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Energy consumption	MySQL	hourly	daily, monthly, yearly	IMP

KPI N°1b			
KPI-Name	Load Forecasting Mean Absolute Percentage Error	**KPI-ID**	LLUC 2a-03 KPI 1b
Description	This KPI is supposed to provide precision performance estimation for Load Forecasting models, similarly to the previous one, but normalized.		
Unit	[%]		
Formula	$$=\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert e_i\rvert}{d_i}$$ where e_i is difference between estimated and real load d_i, and n is number of samples for which KPI is calculated.		

Calculating frequency	This KPI should be evaluated daily or monthly			
Calculation Methodology				
Step	**Description**			
01-	Estimated and real load from the PLATOON platform should be obtained and KPI should be calculated according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Energy consumption	MySQL	hourly	daily, monthly, yearly	IMP

KPI N°2a				
KPI-Name	Load Forecasting Root Mean Square Error		**KPI-ID**	LLUC 2a-03 KPI 2a
Description	This KPI is supposed to provide precision performance estimation for Load Forecasting models.			
Unit	[W]			
Formula	$$= \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}$$ where e_i is difference between estimated and real load, and n is number of samples for which KPI is calculated.			
Calculating frequency	This KPI should be evaluated daily or monthly			
Calculation Methodology				
Step	**Description**			
01-	Estimated and real load from the PLATOON platform should be obtained and KPI should be calculated according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Energy consumption	MySQL	hourly	daily, monthly, yearly	IMP

KPI N°2b			
KPI-Name	Load Forecasting Root Mean Square Error Percentage	**KPI-ID**	LLUC 2a-03 KPI 2b
Description	This KPI is supposed to provide precision performance estimation for Load Forecasting models, similarly to the previous one, but normalized.		
Unit	[%]		
Formula	$$= \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}}{\frac{\sum_{i=1}^{n} d_i}{n}}$$ where e_i is difference between estimated and real load (d_i), and n is number of samples for which KPI is calculated.		
Calculating frequency	This KPI should be evaluated daily or monthly		

Calculation Methodology				
Step	**Description**			
01-	Estimated and real load from the PLATOON platform should be obtained and KPI should be calculated according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Energy consumption	MySQL	hourly	daily, monthly, yearly	IMP

LLUC P 2a-04

KPI N°1a			
KPI-Name	Production Forecasting Mean Absolute Error	**KPI-ID**	LLUC 2a-04 KPI 1a
Description	This KPI is supposed to provide precision performance estimation for Production Forecasting models.		
Unit	[W]		
Formula	$$=\frac{1}{n}\sum_{i=1}^{n}\lvert e_i\rvert$$ where e_i is difference between estimated and real production and n is number of samples for which KPI is calculated.		
Calculating frequency	This KPI should be evaluated daily or monthly		

Calculation Methodology				
Step	**Description**			
01-	Estimated and real production from the PLATOON platform should be obtained and KPI should be calculated according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Energy production	MySQL	hourly	daily, monthly, yearly	IMP

KPI N°1b			
KPI-Name	Production Forecasting Mean Absolute Percentage Error	**KPI-ID**	LLUC 2a-04 KPI 1b
Description	This KPI is supposed to provide precision performance estimation for Production Forecasting models, similarly to the previous one, but normalized.		
Unit	[%]		
Formula	$$= \frac{1}{n}\sum_{i=1}^{n}\frac{\lvert e_i\rvert}{p_i}$$ where e_i is difference between estimated and real production p_i, and n is number of samples for which KPI is calculated.		
Calculating frequency	This KPI should be evaluated daily or monthly		
Calculation Methodology			
Step	**Description**		
01-	Estimated and real production from the PLATOON platform should be obtained and KPI should be calculated according to the formula above.		

Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Energy consumption	MySQL	hourly	daily, monthly, yearly	IMP

KPI N°2a			
KPI-Name	Production Forecasting Root Mean Square Error	**KPI-ID**	LLUC 2a-04 KPI 2a
Description	This KPI is supposed to provide precision performance estimation for Production Forecasting models.		
Unit	[W]		
Formula	$$= \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}$$ where e_i is difference between estimated and real production, and n is number of samples for which KPI is calculated.		

Calculating frequency	This KPI should be evaluated daily or monthly			
Calculation Methodology				
Step	**Description**			
01-	Estimated and real production from the PLATOON platform should be obtained and KPI should be calculated according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Energy consumption	MySQL	hourly	daily, monthly, yearly	IMP

KPI N°2b			
KPI-Name	Production Forecasting Root Mean Square Error Percentage	**KPI-ID**	LLUC 2a-04 KPI 2b
Description	This KPI is supposed to provide precision performance estimation for Production Forecasting models, similarly to the previous one, but normalized.		
Unit	[%]		
Formula	$$= \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}}{\frac{\sum_{i=1}^{n} p_i}{n}}$$ where e_i is difference between estimated and real production (p_i), and n is number of samples for which KPI is calculated.		
Calculating frequency	This KPI should be evaluated daily or monthly		
Calculation Methodology			
Step	**Description**		
01-	Estimated and real production from the PLATOON platform should be obtained and KPI should be calculated according to the formula above.		

Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Energy consumption	MySQL	hourly	daily, monthly, yearly	IMP

LLUC P 2a-05

KPI N°1				
KPI-Name	Increase in PV insertion capacity		**KPI-ID**	KPI-8
Description	Estimate how many PVs can be integrated into LV grid (and where) before a grid limitation is reached (e.g., overvoltage limit). Increase is compared to actual installed PV capacity on LV grid.			
Unit	%			
Formula	$\frac{P_{max}(Vmax)}{P_{installedPV}} * 100\%$ V_{max} according to EN-50160			
Calculating frequency	Once per installation or daily			
Calculation Methodology				
Step	**Description**			
01-	Obtain the maximal daily grid voltage from PMU			
02	For certain period and for estimated worst case scenario condition estimate max grid Voltage.			
03	Calculate the capacity			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Grid voltage	EMS / PMU	50 Hz	months	

LLUC P 2a-07

KPI N°1			
KPI-Name	Saving costs	**KPI-ID**	KPI-8
Description	Algorithms detects abnormal behaviour and predicts the degreation constant. Reduces maintainance costs. It also detects failures.		
Unit	€		

Formula	1. Binary 0 1 Trigger's detection of failure, immediate replacement $(N_{days\ estimate} - N_{days\ after\ detecting failure}) * E_{daily} * price_{of\ electricity}$ 2. Prediction of failure Reduction of Asset Investment costs by minimizing the number of elements to be replaced (PV modules). $\left(\sum_{i=0}^{N_{total}} i - \sum_{i=0}^{N_{string}} i\right) * cost\_of\_module$			
Calculating frequency	daily			
Calculation Methodology				
Step	**Description**			
01-	Obtain correction factor for PV from the service			
02	Obtain historical degradation parameter from the service			
03	Check the values for PV plant/string or inverter level			
04	Compared to the predefined threshold (eg. 75% for module efficiency), 0 or 1 for the inverters			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
E.G., energy consumption	E.g., EMS	daily	daily	

Pilot 2b Electricity Grid Stability, Connectivity and Life cycle

LLUC P 2b-01

KPI N°1				
KPI-Name	Temperature estimation accuracy (%)		**KPI-ID**	01
Description	Hourly temperature accuracy estimation based on estimated temperature (ET) and actual (measured) temperature (AT) for top oil.			
Target Value	5%	**Threshold Value**	10%	
Unit	None			
Formula	(Estimated Temperature-Actual Temperature)/ Actual Temperature (%)			
Calculating frequency	Hourly			
Calculation Methodology				
Step	**Description**			
01-	Model the top oil temperature using machine learning/deep learning.			
02	Compare the prediction obtained using our model with the real values obtained from the sensor.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°2			
KPI-Name	True positives (TP)	**KPI-ID**	02
Description	Number of anomalies detected with early warnings and confirmed with a corrective work order		
Unit	None		

Formula				
Calculating frequency	Hourly			
Calculation Methodology				
Step	**Description**			
01-	Obtain the warnings of needed corrective order given by the model.			
02	Calculate the number of corrective orders that are predicted and applied.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°3				
KPI-Name	False positives (FP)		**KPI-ID**	03
Description	Early warnings with no associated corrective work order			
Unit	None			
Formula				
Calculating frequency	Hourly			
Calculation Methodology				
Step	**Description**			
01-	Obtain the warnings of needed corrective order given by the model.			
02	Calculate the number of corrective orders that are predicted but not applied.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°4				
KPI-Name	False negatives (FN)	**KPI-ID**	04	
Description	Corrective work order without a previous early warning.			
Unit	None			
Formula				
Calculating frequency	Hourly			
Calculation Methodology				
Step	**Description**			
01-	Obtain the warnings of needed corrective order given by the model.			
02	Calculate the number of corrective orders that are not predicted and applied.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°5			
KPI-Name	True Negatives (TN)	**KPI-ID**	05
Description	No early warning and no work order		
Unit	None		
Formula			
Calculating frequency	Hourly		

Calculation Methodology				
Step	**Description**			
01-	Obtain the warnings of needed corrective order given by the model.			
02	Calculate the number of corrective orders that are not predicted and not applied.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°6				
KPI-Name	Specificity (%)		**KPI-ID**	06
Description	Proportion of true negatives relative to all negative cases.			
Unit				
Formula	(TN/(TN+FP))			
Calculating frequency	Hourly			
Calculation Methodology				
Step	**Description**			
01-	Obtain the proportion of transformers that does not need a corrective order that are correctly identified.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°7			
KPI-Name	Sensitivity (%)	**KPI-ID**	07

Description	Proportion of actual needed corrective order correctly identified			
Unit	None			
Formula	(TP/(TP+FN))			
Calculating frequency	Hourly			
Calculation Methodology				
Step	**Description**			
01-	Obtain the proportion of transformers that need a corrective order that are correctly identified.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°8			
KPI-Name	Cohen's Kappa (%)	**KPI-ID**	08
Description	Measurement of matches in the predictive tool discounting the probability of randomly matching		
Unit	None		
Formula	$K = \frac{p_0 - p_e}{1 - p_e}$, where $p_0 = \frac{TP+TN}{TP+TN+FP+FN}$ and $p_e = p_{Yes} + p_{No} = \frac{TP+FP}{TP+TN+FP+FN} \frac{TP+FN}{TP+TN+FP+FN} + \frac{FP+TN}{TP+TN+FP+FN} \frac{FN+TN}{TP+TN+FP+FN}$		
Calculating frequency	Hourly		
Calculation Methodology			
Step	**Description**		
01-	Calculate the TP,TN,FP,FN.		
02	Apply the formula to obtain the needed corrective orders not well predicted randomly.		

Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°9			
KPI-Name	Savings (€)	**KPI-ID**	09
Description	Cumulative measurement of savings associated to True Positives considering: a) Avoided breakdown consequences + b) Downtime cost		
Unit	€		
Formula			
Calculating frequency	Hourly		
Calculation Methodology			
Step	**Description**		
01-	Calculate the breakdown caused by the failure that has been predicted and corrected and the downtime that it should have caused.		
02	Obtain the monetary compensation that this downtime and breakdown should have caused.		

Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°10			
KPI-Name	Additional Costs (€)	**KPI-ID**	10
Description	Increased costs due to maintenance activities associated to False Positives. They should be subtracted from Savings to get the net value.		
Unit	€		

Formula				
Calculating frequency	Hourly			
Calculation Methodology				
Step	**Description**			
01-	Obtain the cost of maintenance caused due to false positives.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°11			
KPI-Name	Anticipation time (days)	**KPI-ID**	11
Description	For each True Positive it represents the delta Time between the moment of detection and the time of failure.		
Unit	Seconds|Minutes|Days		
Formula			
Calculating frequency	Hourly		
Calculation Methodology			
Step	**Description**		
01-	Predict the failure dates of the transformers and obtain the difference between the predicted date and the real failure dates.		

Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°12

KPI-Name	Risk decrease (€)		**KPI-ID**	12
Description	Risk decrease comparing risk-based maintenance supported by the tool to the ordinary preventive maintenance (equal maintenance expenditure is assumed in both cases)			
Unit	€			
Formula				
Calculating frequency	Hourly			
Calculation Methodology				
Step	**Description**			
01-	Calculate the ordinary risk of failure and predicted risk of failure. Multiply this by the cost of maintenance.			
02	Obtain the difference between the cost * risk between the tool and the actual maintenance strategy.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°13			
KPI-Name	Maintenance cost savings (€)	**KPI-ID**	13
Description	Maintenance cost savings comparing risk-based maintenance supported by the tool to the ordinary preventive maintenance (equal risk level is assumed in both cases)		
Unit	€		
Formula			
Calculating frequency	Hourly		
Calculation Methodology			
Step	**Description**		
01-	Calculate the costs of ordinary maintenance and predicted maintenance.		

02	Obtain the difference between predicted maintenance cost and ordinary maintenance cost.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°14				
KPI-Name	Useful Life Extension (years)		**KPI-ID**	14
Description	Based on the estimation of the RUL (Remaining Useful Time) it indicates the achievable extension of life relative to that indicated by the manufacturer			
Unit	Years/months			
Formula	Previous RUL- loss of life since last RUL calculation			
Calculating frequency	Daily			
Calculation Methodology				
Step	**Description**			
01-	Apply the standards to obtain the HST from the TOT			
02	Apply the standards to calculate the useful life decreasement from the TOT.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Transformer Temperature and load	Transformer Temperature sensors database S02	15 min	unknown	SAMPOL

KPI N°15			
KPI-Name	Mean Average Percentage Error	**KPI-ID**	15

Description	Accuracy of the predicted value compared to real value in healthy operating conditions using the Mean Absolute Percentage Error (MAPE).			
Target Value	Target value: 0%	Threshold Value 5%	The value used to assess the effectiveness/efficiency performance of the monitored process. RMS error	
Formula	(Abs(predicted value of modelled parameter – true value)/true value) * 100			
Calculating frequency	Each data set			
Calculation Methodology				
Step	**Description**			
01-	Predict the value of modelled parameter			
02	Compare to the real value according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Signals used as input for the models	SAMPOL online data	10 min	Data corresponding to training range for the model.	SAMPOL

KPI N°16			
KPI-Name	Mean Average Percentage Error	**KPI-ID**	16
Description	Accuracy of the predicted value compared to real value in healthy operating conditions using the Mean Absolute Percentage Error (MAPE).		
Target Value	Target value: 0%	Threshold Value 5%	The value used to assess the effectiveness/efficiency performance of the monitored process. RMS error
Formula	(Sum of N samples((Abs(predicted value of modelled parameter – true value)/true value) * 100)/N		
Calculating frequency	Each data set		
Calculation Methodology			

Step	Description			
01-	Predict the value of modelled parameter			
02	Compare to the real value according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Signals used as input for the models	SAMPOL online data	10 min	Data corresponding to training range for the model.	SAMPOL

KPI N°17			
KPI-Name	Mean Error	**KPI-ID**	17
Description	Accuracy of the predicted value compared to real value in healthy operating conditions using the Mean Absolute Percentage Error (MAPE).		
Target Value	Target value: 0	Threshold Value 5% of actual value	The value used to assess the effectiveness/efficiency performance of the monitored process. RMS error
Unit	Percentage error		
Formula	(Sum of N samples(predicted value of modelled parameter – true value))/N		
Calculating frequency	Each data set		
Calculation Methodology			
Step	**Description**		
01-	Predict the value of modelled parameter		
02	Compare to the real value according to the formula above.		
Data Source			

Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner

Signals used as input for the models	SAMPOL online data	10 min	Data corresponding to training range for the model.	SAMPOL

KPI N°18				
KPI-Name	Mean Absolute Error		**KPI-ID**	18
Description	Accuracy of the predicted value compared to real value in healthy operating conditions using the Mean Absolute Percentage Error (MAPE).			
Target Value	Target value: 0	Threshold Value 5% of actual value	The value used to assess the effectiveness/efficiency performance of the monitored process. RMS error	
Formula	(Sum of N samples(Abss(predicted value of modelled parameter – true value)))/N			
Calculating frequency	Each data set			
Calculation Methodology				
Step	**Description**			
01-	Predict the value of modelled parameter			
02	Compare to the real value according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Signals used as input for the models	SAMPOL online data	10 min	Data corresponding to training range for the model.	SAMPOL

KPI N°19			
KPI-Name	Mean Squared Error	**KPI-ID**	19
Description	Accuracy of the predicted value compared to real value in healthy operating conditions using the Mean Absolute Percentage Error (MAPE).		

Target Value	Target value: 0		Threshold Value 5% of actual value	The value used to assess the effectiveness/efficiency performance of the monitored process. RMS error
Formula	(Sum of N samples((predicted value of modelled parameter – true value)^2))/N			
Calculating frequency	Each data set			
Calculation Methodology				
Step	**Description**			
01-	Predict the value of modelled parameter			
02	Compare to the real value according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Signals used as input for the models	SAMPOL online data	10 min	Data corresponding to training range for the model.	SAMPOL

KPI N°20			
KPI-Name	Root Mean Squared Error	**KPI-ID**	20
Description	Accuracy of the predicted value compared to real value in healthy operating conditions using the Mean Absolute Percentage Error (MAPE).		
Target Value	Target value: 0	Threshold Value 5% of actual value	The value used to assess the effectiveness/efficiency performance of the monitored process. RMS error
Formula	((Sum of N samples((predicted value of modelled parameter – true value)^2))/N)^0.5		
Calculating frequency	Each data set		
Calculation Methodology			
Step	**Description**		

01-	Predict the value of modelled parameter			
02	Compare to the real value according to the formula above.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Signals used as input for the models	SAMPOL online data	10 min	Data corresponding to training range for the model.	SAMPOL

KPI N°21					
KPI-Name	Correlation Coefficient R2		**KPI-ID**	21	
Description	Accuracy of the predicted value compared to real value in healthy operating conditions using the Mean Absolute Percentage Error (MAPE).				
Target Value	Target value: 1	Threshold Value 0.85		The value used to assess the effectiveness/efficiency performance of the monitored process. RMS error	
Formula	Estimated Covariance(predicted value of modelled parameter, true value)/(Estimated Standard deviation predicted value X Estimated Standard deviation true value)				
Calculating frequency	Each data set				
Calculation Methodology					
Step	**Description**				
01-	Predict the value of modelled parameter				
02	Compare to the real value according to the formula above.				
Data Source					
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner	
Signals used as input for the models	SAMPOL online data	10 min	Data corresponding to training range for the model.	SAMPOL	

LLUC P 2b-02

KPI N°1					
KPI-Name	Global Losses Energy Percentage		**KPI-ID**	NTL-KPI-01	
Description	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).				
Target Value	30%		**Threshold Value**	35%	
Unit	None				
Formula	NTL-KPI-01 = NTL-KPI-02 + NTL-KPI-03				
Calculating frequency	Hourly/Daily				
Calculation Methodology					
Step	**Description**				
01-	Calculate the total consumption of all customers.				
02	Calculate the percentage of the customers consumptions over the energy provided by the power transformer.				
Data Source					
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner	
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00, 2020-10-16 04:00:00,	SAMPOL	

KPI N°2				
KPI-Name	NTL Energy Percentage		**KPI-ID**	NTL-KPI-02
Description	Percentage of the energy that is provided from a MV substation or LV CT that is lost due to NTL			
Target Value	15%		**Threshold Value**	20%
Unit	None			

Formula	NTL-KPI-02 = NTL-KPI-04 + NTL-KPI-05			
Calculating frequency	Hourly/Daily			
Calculation Methodology				
Step	**Description**			
01-	Calculate the NTL caused by consumers and non-consumers.			
02				
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00, 2020-10-16 04:00:00,	SAMPOL

KPI N°3			
KPI-Name	TL Energy Percentage	**KPI-ID**	NTL-KPI-03
Description	Percentage of the energy that is provided from a MV substation or LV CT that is lost due to TL		
Target Value	**10%**	**Threshold Value**	**15%**
Unit	None		
Formula	None		
Calculating frequency	Hourly/Daily		
Calculation Methodology			
Step	**Description**		
01-	Obtain the characteristics of the distribution grid.		
02	Calculate the expected technical loses.		
Data Source			

Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00, 2020-10-16 04:00:00,	SAMPOL

KPI N°4			
KPI-Name	Customer NTL Energy Percentage	**KPI-ID**	NTL-KPI-04
Description	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.		
Target Value	**10%**	**Threshold Value**	**15%**
Unit	None		
Formula	None		
Calculating frequency	Hourly/Daily		
Calculation Methodology			
Step	**Description**		
01-	Subtract the technical loses to the total loses.		
02	Obtain the part of the result that can be imputed to customers.		

Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00, 2020-10-16 04:00:00,	SAMPOL

KPI N°5			
KPI-Name	Non-Customer NTL Energy Percentage	**KPI-ID**	NTL-KPI-05
Description	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.		
Target Value	10%	**Threshold Value**	15%
Unit	None		
Formula	None		
Calculating frequency	Hourly/Daily		
Calculation Methodology			

Step	**Description**			
01-	Subtract the technical loses to the total loses.			
02	Obtain the part of the result that can not be imputed to customers.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00,2020-10-16 04:00:00,	SAMPOL

KPI N°6				
KPI-Name	True positives (TP)		**KPI-ID**	NTL-KPI-06
Description	Number of customers identified as fraud authors in the NTL identification scenario which are verified to be committing fraud			
Target Value	7.45%		**Threshold Value**	3.66%
Unit	None			
Formula	None			
Calculating frequency	Hourly/Daily			
Calculation Methodology				
Step	**Description**			
01-	Obtain the customers that can be causing NTL using the developed models and identify if they are really causing NTL			
02	Calculate the number of customers that are predicted as causing NTL and are really causing NTL.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00,2020-10-16 04:00:00,	SAMPOL

KPI N°7				
KPI-Name	False positives (FP)		**KPI-ID**	NTL-KPI-07
Description	Number of customers identified as fraud authors in the NTL identification scenario which are not committing fraud, as result of a verification action			
Target Value	8.96%	**Threshold Value**	11.44%	
Unit	None			
Formula	None			
Calculating frequency	Hourly/Daily			
Calculation Methodology				
Step	**Description**			
01-	Obtain the customers that can be causing NTL using the developed models and identify if they are really causing NTL			
02	Calculate the number of customers that are predicted as causing NTL and are not causing NTL.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Data obtained from the Parc	S02	1 hour	2016-10-19 00:00:00,2020-10-16 04:00:00,	SAMPOL

Bit distribution Grid				

KPI N°8				
KPI-Name	False negatives (FN)		**KPI-ID**	NTL-KPI-08
Description	Number of customers which are not identified as fraud authors in the NTL identification scenario but are really committing fraud			
Target Value	2.29%		**Threshold Value**	4.57%
Unit	None			
Formula	None			
Calculating frequency	Hourly/Daily			
Calculation Methodology				
Step	**Description**			
01-	Obtain the customers that can be causing NTL using the developed models and identify if they are really causing NTL			
02	Calculate the number of customers that are predicted as not causing NTL and are really causing NTL.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00,2020-10-16 04:00:00,	SAMPOL

KPI N°9			
KPI-Name	True negatives (TN)	**KPI-ID**	NTL-KPI-09

Description	Number of customers which are not identified as fraud authors in the NTL identification scenario, and are not really committing fraud.			
Target Value	81.3%	**Threshold Value**	73.19%	
Unit	None			
Formula	None			
Calculating frequency	Hourly/Daily			
Calculation Methodology				
Step	**Description**			
01-	Obtain the customers that can be causing NTL using the developed models and identify if they are really causing NTL			
02	Calculate the number of customers that are predicted as not causing NTL and are really not causing NTL.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00,2020-10-16 04:00:00,	SAMPOL

KPI N°10			
KPI-Name	Specificity (%)	**KPI-ID**	NTL-KPI-10
Description	Proportion of true negatives relative to all negative cases.		
Target Value	70%	**Threshold Value**	45%
Unit	None		
Formula	(TN/(TN+FP))		
Calculating frequency	Hourly/Daily		

Calculation Methodology				
Step	**Description**			
01-	Obtain the proportion of negative cases of NTL that are correctly identified.			
02				
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00,2020-10-16 04:00:00,	SAMPOL

KPI N°11				
KPI-Name	Sensitivity (%)		**KPI-ID**	NTL-KPI-11
Description	Proportion of actual positives cases of NTL correctly identified.			
Target Value	52%		**Threshold Value**	40%
Unit	None			
Formula	(TP/(TP+FN))			
Calculating frequency	Hourly/Daily			
Calculation Methodology				
Step	**Description**			
01-	Obtain the proportion of positives that are correctly identified.			
02				
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner

Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00,2020-10-16 04:00:00,	SAMPOL

KPI N°12					
KPI-Name	Cohen's Kappa (%)			**KPI-ID**	NTL-KPI-12
Description	Measurement of matches in the NTL identification scenario discounting the probability of randomly matching.				
Target Value		45%	**Threshold Value**		40%
Unit	None				
Formula	, where and				
Calculating frequency	Hourly/Daily				
Calculation Methodology					
Step	**Description**				
01-	Calculate the TP,TN,FP,FN.				
02	Apply the formula to obtain the NTL identifications not well predicted randomly.				
Data Source					
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner	
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00,2020-10-16 04:00:00,	SAMPOL	

KPI N°13			
KPI-Name	Economic Savings	**KPI-ID**	NTL-KPI-13

Description	Economic savings due to detected non-technical losses.			
Unit	None			
Formula	None			
Calculating frequency	Hourly/Daily			
Calculation Methodology				
Step	**Description**			
01-	Obtain the costs of energy production and impute the percentage of NTL to this costs.			
02				
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Data obtained from the Parc Bit distribution Grid	S02	1 hour	2016-10-19 00:00:00, 2020-10-16 04:00:00,	SAMPOL

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

LLUC P-3a-01

KPI N°1			
KPI-Name	Deviation to target comfort during occupancy time	**KPI-ID**	KPI-1
KPI-Type	Technical/Business		
Description	The thermal comfort in the building is evaluated thanks to air temperature. During occupancy time, the objective is to be within the range of comfort defined by the building manager. The deviations to this range will be monitored during occupancy periods.		
Target Value	0.5°C to comfort range	**Threshold Value**	2°C to comfort range

Rounding	Rounding to 0.01
Unit	°C
Formula	During occupancy periods : $$\sum_{t=0}^{nb_{timestep}} \sum_{p=0}^{nb_{point}} \frac{error\left(T(t,p), Target_{range}\right) * w(p)}{nb_{timestep} * nb_{point} * \sum_{p=0}^{nb_{point}} w(p)}$$ T(t,p): temperature of the point p at the timestep t (during occupancy period) w(p) : weight of the point p (if any, default 0) Target_range : Interval of room temperature defined by the building manager that is considered as “acceptable”. Typically : [20°C-25°C] nb_timestep : number of regular timestep (hourly or less) in the period analyzed. nb_point : number of temperature sensor points
Calculating frequency	According to need : daily, weekly, monthly …
Calculation Methodology	
Step	**Description**
01	Choice of a period, or calculation for default periods (days, weeks, months, years)
02	For the given period considered (week, month, year), identification of the occupancy periods for the different zones defined in the building.
03	Request of the temperature for the different occupancy periods of the different zones and application of the formula

Data Source

Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Occupancy in the different zones	ENGIE IT – data occupancy	15 min	Ongoing in real time	ENGIE
Temperature in the different zones	BMS	15 min ?	Ongoing in real time	ENGIE
Config pilot	config	-	-	ENGIE

KPI N°2			
KPI-Name	Unnecessary HVAC heating emission	**KPI-ID**	KPI-2

KPI-Type	Technical/Business			
Description	Evaluate the amount of energy emission (heating or cooling) that could be considered as unnecessary regarding the actual building occupancy, especially when : ■ Preheating or precooling time over-anticipation ■ Heating/cooling but no one present for the rest of the day. The percentage of valve opening, attributed to a specific weight will be considered as the measure of the unnecessary heating or cooling emission.			
Target Value	<10%	**Threshold Value**	30%	
Rounding	Rounding to 0.1%			
Unit	%			
Formula	$\frac{\sum_{v=0}^{nb_{nb\_valve}} \sum_{t \in [unecessary\ heating]} Op_h(v,t) * P_{max,h}(v)}{\sum_{v=0}^{nb_{nb_{valve}}} \sum_{t \in [whole\ period]} Op_h\ (v,t) * P_{max,h}(v)}$ With : [Unnecessary heating] : ▪ Last period at the end of the day when the zone is unoccupied but heating still happening. ▪ First period of the day when the zone is unoccupied, heating is happening, but preheating period is finished (Tzone-Tsetpoint<Tref_lim) Op_h (v,t) : opening of the valve v for heating during the time step t $P_{max,h}$ (v) : Maximum power of the heat emissions behind the valve v			
Calculating frequency	According to need : daily, weekly, monthly …			
Calculation Methodology				
Step	**Description**			
01-	Choice of a period, or calculation for default periods (days, weeks, months, years)			
02	Identification of time periods for each valve where : - Last period at the end of the day when the zone is unoccupied, but heating still happening (over anticipation) - First period of the day when the zone is unoccupied, heating is happening, but preheating period is finished (Tzone-Tsetpoint<Tref_lim)			
03	For the different periods identified, and for the different zones and valves considered, the above formula can be calculated			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**

Temperature in the different zones	BMS	15 min ?	Ongoing in real time	ENGIE
Valve opening in the different zones	BMS	15 min ?	Ongoing in real time	ENGIE
Temperature setpoints in the different zones	BMS	15 min ?	Ongoing in real time	ENGIE
Config pilot	config	-	-	ENGIE

KPI N°3			
KPI-Name	Unnecessary HVAC cooling emission	**KPI-ID**	KPI-2bis
KPI-Type	Technical/Business		
Description	Evaluate the amount of energy emission (heating or cooling) that could be considered as unnecessary regarding the actual building occupancy, especially when : ■ Preheating or precooling time over-anticipation ■ Heating/cooling but no one present for the rest of the day. The percentage of valve opening, attributed to a specific weight will be considered as the measure of the unnecessary heating or cooling emission.		
Target Value	<10%	**Threshold Value**	30%
Rounding	Rounding to 0.1%		
Unit	%		
Formula	$\frac{\sum_{v=0}^{nb_{nb\_valve}} \sum_{t \in [necessary\ heating]} Op_c(v,t) * P_{max,c}(v)}{\sum_{v=0}^{nb_{nb_{valve}}} \sum_{t \in [whole\ period]} Op_c(v,t) * P_{max,c}(v)}$ With : [Unnecessary heating periods] : ▪ Last period at the end of the day when the zone is unoccupied, but heating still happening. ▪ First period of the day when the zone is unoccupied, heating is happening, but preheating period is finished (Tzone-Tsetpoint<Tref_lim) Op_c (v,t) : opening of the valve v for cooling during the time step t $P_{max,c}$ (v) : Maximum power of the cooling emissions behind the valve v		
Calculating frequency	According to need : daily, weekly, monthly …		
Calculation Methodology			

Step	**Description**			
01-	Choice of a period, or calculation for default periods (days, weeks, months, years)			
02	Identification of time periods for each valve where : - Last period at the end of the day when the zone is unoccupied, but cooling still happening (over anticipation) - First period of the day when the zone is unoccupied, cooling is happening, but precooling period is finished (Tzone-Tsetpoint<Tref_lim)			
03	For the different periods identified, and for the different zones and valves considered, the above formula can be calculated			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Temperature in the different zones	BMS	15 min ?	Ongoing in real time	ENGIE
Valve opening in the different zones	BMS	15 min ?	Ongoing in real time	ENGIE
Temperature setpoints in the different zones	BMS	15 min ?	Ongoing in real time	ENGIE
Config pilot	config	-	-	ENGIE

KPI N°4			
KPI-Name	Gain on heating consumption	**KPI-ID**	KPI-3
KPI-Type	Technical/Business		
Description	Climate corrected gain on heating energy consumption in comparison with the consumption of the previous year		
Target Value	>10%	**Threshold Value**	0%
Rounding	0.1%		
Unit	%		
Formula	For a given period : $$\frac{Cs_{ht,p} * HDD(p, Text(p)) - Cs_{ht,p\_py} * HDD(p\_py, Text(p\_py))}{Cs_{ht,p\_py} * HDD(p\_py, Text(p\_py))}$$		

	With : $Cs_{ht,p}$: energy consumption for heating during the period p Cs_{ht,p_py} : energy consumption for heating during the period p but the previous year HDD(p,Text(p)) : Heating degree day for the period p and the external temperature over the period HDD(p,Text(p)) : Heating degree day for the period p of the previous year and the external temperature during this period ***à cf. formula of calculation HDD at the end of the document***.
Calculating frequency	On request
Calculation Methodology	
Step	**Description**
01-	Choice of a period, or calculation for default periods (days, weeks, months, years) *à Data of the previous year over the same period has to be available*
02	Application of the formula

Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Energy consumption for heating	BMS	15 min ?	Ongoing in real time	ENGIE
External temperature setpoint	BMS/	1h or less	Defined periods	ENGIE

KPI N°5			
KPI-Name	Gain on cooling consumption	**KPI-ID**	KPI-4
KPI-Type	Technical/Business		
Description	Climate corrected gain on cooling energy consumption in comparison with the consumption of the previous year		
Target Value	>10%	**Threshold Value**	0%
Rounding	0.1%		
Unit	%		
Formula	For a given period :		

	$$\frac{Cs_{c,p} * CDD\big(p, Text(p)\big) - Cs_{c,p\_py} * CDD\big(p\_py, Text(p\_py)\big)}{Cs_{c,p\_py} * CDD\big(p\_py, Text(p\_py)\big)}$$ With : $Cs_{ht,p}$: energy consumption for cooing during the period p Cs_{ht,p_py} : energy consumption for cooling during the period p but the previous year CDD(p,Text(p)) : cooling degree day for the period p and the external temperature over the period CDD(p,Text(p)) : cooling degree day for the period p of the previous year and the external temperature during this period *cf. formula of calculation CDD at the end of the document*.			
Calculating frequency	On request			
Calculation Methodology				
Step	**Description**			
01-	Choice of a period, or calculation for default periods (days, weeks, months, years) *Data of the previous year over the same period has to be available*			
02	Application of the formula			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Energy consumption for cooling	BMS	15 min ?	Ongoing in real time	ENGIE
External temperature setpoint	BMS/	1h or less	Defined periods	ENGIE

LLUC P-3a-02: Provide Demand Response services through building inertia and HVAC controls

KPI N°1			
KPI-Name	Mean error on heating load prediction	**KPI-ID**	KPI-1
KPI-Type	Technical/Business		
Description	Mean error (%) on the HVAC heating load prediction calculated every 30min as the errors between the predicted and the realized energy consumption and the predicted one (when HVAC is operating).		

Target Value	Error <10%	**Threshold Value**	Mean error above 20%
Rounding	0.1%		
Unit	%		
Formula	$$\sum_{t=0}^{nb_{timetep}} \frac{Cs_{ht,model}(t) - Cs_{ht,real}(t)}{Cs_{ht,real}(t) * nb_{timestep}}$$ With : $Cs_{ht,model}(t)$: heating consumption predicted by the model for the timestep t $Cs_{ht, real}(t)$: real heating consumption measured for the timestep t		
Calculating frequency	Once, daily, weekly, monthly …		
Calculation Methodology			
Step	**Description**		
01-	Choice of a period, or calculation for default periods (days, weeks, months, years)		
02	Application of formula		
Data Source			

Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Energy consumption for heating	BMS	30 min	Ongoing in real time	ENGIE
Predicted energy consumption	Platoon tool	30 min	-	ENGIE

KPI N°2			
KPI-Name	Mean error on cooling load prediction	**KPI-ID**	KPI-1bis
KPI-Type	Technical/Business		
Description	Mean error (%) on the HVAC cooling load prediction calculated every 30min as the errors between the predicted and the realized energy consumption and the predicted one (when HVAC is operating).		
Target Value	Error <10%	**Threshold Value**	Mean error above 20%
Rounding	0.1%		

Unit	%			
Formula	$$\sum_{t=0}^{nb_{timetep}} \frac{Cs_{c,model}(t) - Cs_{c,real}(t)}{Cs_{c,real}(t) * nb_{timestep}}$$ With : $Cs_{c,model}(t)$: cooling consumption predicted by the model for the timestep t $Cs_{c, real}(t)$: real cooling consumption measured for the timestep t			
Calculating frequency	Once, daily, weekly, monthly …			
Calculation Methodology				
Step	**Description**			
01-	Choice of a period, or calculation for default periods (days, weeks, months, years)			
02	Application of formula			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Energy consumption for cooling	BMS	30 min	Ongoing in real time	ENGIE
Predicted energy consumption	Platoon tool	30 min	-	ENGIE

KPI N°3			
KPI-Name	95-percentile error on heating load prediction	**KPI-ID**	KPI-2
KPI-Type	Technical/Business		
Description	95-percentile Error on the HVAC heating load prediction calculated every 30min as the errors between the predicted and the realized energy consumption and the predicted one (when HVAC is operating).		
Target Value	Error <20%	**Threshold Value**	Mean error above 40%
Rounding	0.1%		
Unit	%		
Formula	Error on each timestep		

	$$Err(t) = \frac{Cs_{ht,model}(t) - Cs_{ht,real}(t)}{Cs_{ht,real}(t)}$$ Then, identification of the 95-percentile of the Err(t) over the period With : $Cs_{ht,model}(t)$: heating consumption predicted by the model for the timestep t $Cs_{ht,\ real}(t)$: real heating consumption measured for the timestep t			
Calculating frequency	Once, daily, weekly, monthly …			
Calculation Methodology				
Step	**Description**			
01-	Choice of a period, or calculation for default periods (days, weeks, months, years)			
02	Application of the formula			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Energy consumption for heating	BMS	30 min	Ongoing in real time	ENGIE
Predicted energy consumption	Platoon tool	30 min	-	ENGIE

KPI N°4			
KPI-Name	95-percentile error on cooling load prediction	**KPI-ID**	KPI-2bis
KPI-Type	Technical/Business		
Description	Error (%) on the HVAC cooling load prediction calculated every 30min as the errors between the predicted and the realized energy consumption, divided by the predicted one (when HVAC is operating). The error can be characterized over the period: mean, standard deviations, daily distribution, seasonal distribution.		
Target Value	Error <20%	**Threshold Value**	Mean error above 40%
Rounding	0.1%		
Unit	%		

Formula	Error on each timestep $$Err(t) = \frac{Cs_{c,model}(t) - Cs_{c,real}(t)}{Cs_{c,real}(t)}$$ Then, identification of the 95-percentile of the Err(t) over the period With : $Cs_{c,model}(t)$: cooling consumption predicted by the model for the timestep t $Cs_{c,\,real}(t)$: real cooling consumption measured or the timestep t			
Calculating frequency	Once, daily, weekly, monthly …			
Calculation Methodology				
Step	**Description**			
01-	Choice of a period, or calculation for default periods (days, weeks, months, years)			
02	Application of formula			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Energy consumption for cooling	BMS	30 min	Ongoing in real time	ENGIE
Predicted energy consumption	Platoon tool	30 min	-	ENGIE

KPI N°5			
KPI-Name	Error on the flexibility prediction	**KPI-ID**	KPI-4
KPI-Type	Technical/Business		
Description	Error (%) on the prediction of “flexibility available” on the building, in term of time of interruption of heating or cooling in the building, during flexibility event implemented in the building.		
Target Value	Target : 10%	**Threshold Value**	30%
Rounding	0.1%		
Unit	%		
Formula	$$\frac{\mathrm{Time}_{\mathrm{int,model}} - \mathrm{Time}_{\mathrm{int,real}}}{\mathrm{Time}_{\mathrm{int,real}}}$$		

	Time_(int,model) : time of interruption planned in the model Time_(int, real) : actual time of interruption that was actually implemented in the building.
Calculating frequency	After interruption event …
Calculation Methodology	
Step	**Description**
01-	Application of the formula

Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Predicted time of interruption	Platoon tool	30 min	-	ENGIE
Interruption	BMS	-	-	ENGIE

KPI N°6			
KPI-Name	Mean error on HVAC load prediction for days with load shifting programs	**KPI-ID**	KPI-5
KPI-Type	Technical/Business		
Description	Mean error (%) on the HVAC load prediction calculated every 30min as the errors between the predicted and the realized energy consumption and the predicted one (when HVAC is operating), in case of the implementation of a load shifting program (not the usual building operation)		
Target Value	Error <10%	**Threshold Value**	20%
Rounding	0.1%		
Unit	%		
Formula	$$\sum_{t=0}^{nb_{timetep}} \frac{Cs_{ht,c,model}(t) - Cs_{ht,c,real}(t)}{Cs_{ht,c,real}(t) * nb_{timestep}}$$ With : $Cs_{ht,c,model}(t)$: heating or cooling consumption predicted by the model for the timestep t $Cs_{ht,\ real}(t)$: real heating or cooling consumption measured for the timestep t		

Calculating frequency	For a day after implementation of load shifting program			
Calculation Methodology				
Step	**Description**			
01	Application of the formula			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Energy consumption for heating	BMS	30 min	Ongoing in real time	ENGIE
Energy consumption for cooling	BMS	30 min	Ongoing in real time	ENGIE
Predicted energy consumption	Platoon tool	30 min	-	ENGIE

Pilot 3b - PI Advanced Energy Management System and Spatial (Multi-Scale) Predictive Models in the Smart City

LLUC-01

KPI N°1			
KPI-Name	Forecast Error	**KPI-ID**	PI_KPI01
KPI-Type	Technical		
Description	The KPI calculates the % of deviation between the energy consumption forecast and the actual consumption in the building. The KPI checks how closely the predictive model adheres to reality - Effectiveness		
Target Value	+-5%	**Threshold Value**	+-20%
Rounding	round off to 0% for values between 0.00 and 0.49 and to 1% for values above		
Unit	Kilowatt per hour (KWh)		
Formula	$$\mathbf{FE_i} = \frac{(F_{F,i} - F_{A,i})}{F_{A,i}} * 100$$ $$\mathbf{FE_M} = \frac{1}{N}\sum_i FE_i$$ FE_i= Forecast Error % of building "i" $F_{F,i}$ = Forecasted value of building "i" $F_{A,i}$ = Actual value of building "i" N = number of buildings utilized for the KPI calculation		
Calculating frequency	Weekly (Alert if Threshold Value is exceeded)		
Calculation Methodology			
Step	**Description**		
01	Select the time range and the specific building and the perimeter of calculation: 1. Total energy consumption or 2. Total energy consumption for Specific line (cooling/heating) in the building		
02	Calculate the forecast taking into account: – Real data consumption – Temperature and Humidity (internal and external) – Number of Customers and Employees – Building open hours and shift		

	– Building Climate Zone, m^3			
03	Get the Real consumption data (of the target month) taking into account: - The full month active energy consumption (Total Active Energy) of the selected building or of a specific line (Detailed Energy Consumption)			
04	Apply the formula			
05	The formula will be applied for each one of the selected buildings, then arithmetic mean will be calculated from these selected values.			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Office Registry	Building Data	At starting up and then occasionally, when changes occur	No Temporal Range	Poste Italiane
Building Calendar	Building Data	Monthly	From 01/01/2018	Poste Italiane
Total Active Energy consumption	Energy Consumption	Monthly		Poste Italiane
Detailed Energy Consumption DL_102	Energy Consumption	Monthly	TBD	Poste Italiane
Detailed Energy Consumption	Energy Consumption	Daily	From 01/01/2018	Poste Italiane
Temperature, Humidity	Weather		From 01/01/2018	External Services
Customers Number	Occupancy	Monthly	From 01/01/2018	Poste Italiane
Employees Number	Occupancy	Monthly	From 01/01/2018	Poste Italiane

KPI N°2			
KPI-Name	Building Benchmarking BtI_LY	**KPI-ID**	PI_KPI02
KPI-Type	Business		
Description	The KPI calculate, in % value, the difference in Energy consumption of a building with itself during the time. The comparison will be made with the previous year consumption		
Target Value	+-10%	**Threshold Value**	+-20%

Rounding	round off to 0% for values between 0.00 and 0.49 and to 1% for values above			
Unit	Kilowatt per hour (KWh)			
Formula	$$\mathbf{B_{BTI_{LY},i}} = \frac{(\mathrm{EC_{y,i}} - \mathrm{EC_{y-1,i}})}{\mathrm{EC_{y-1,i}}} * 100$$ $$\mathbf{B_{BTI_{LY},M}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}} \mathrm{B_{BTI_{LY},i}}$$ BBTILY,i = Building "i" last year comparison (with itself) ECy,i = Energy Consumption in the time range for building "i" ECy-1, i= Energy Consumption in the same time range of the previous year for building "i" N = number of buildings utilized for the KPI calculation			
Calculating frequency	Weekly			
Calculation Methodology				
Step	**Description**			
01	The calculation takes into account: a. The time range (reference week) b. The time range for benchmark (the same week of the previous year) c. The building d. The perimeter of the analysis: Total energy consumption, or, where available the energy consumption of heating or cooling, lighting			
02	The formula will be applied for each one of the selected buildings, then arithmetic mean will be calculated from these selected values.			
03	Normalize both the consumptions by the comfort level (where available) Comfort level is a range of internal temperature and humidity that must be complied Comfort level = f (internal temperature, internal humidity) (Internal humidity, internal temperature) = f (external humidity, external temperature)			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Office Registry	Building Data	At starting up and then occasionally, when changes occur	No Temporal Range	Poste Italiane
Building Calendar	Building Data	Monthly	From 01/01/2018	Poste Italiane
Detailed Energy Consumption	Energy Consumption	Daily	From 01/01/2018	Poste Italiane

Detailed Energy Consumption DL_102	Energy Consumption	Monthly	TBD	Poste Italiane
Total Active Energy consumption	Energy Consumption	Monthly	From 01/01/2018	Poste Italiane
Temperature, Humidity	Weather			External Services

KPI N°3			
KPI-Name	Building Benchmarking BtI_LWs	**KPI-ID**	PI_KPI03
KPI-Type	Business		
Description	The KPI calculate, in % value, the difference in Energy consumption of a building with itself during the time. The comparison will be made with the two previous weeks comsumptions		
Target Value	+-10%	**Threshold Value**	+-20%
Rounding	round off to 0% for values between 0.00 and 0.49 and to 1% for values above		
Unit	Kilowatt per hour (KWh)		
Formula	$$\mathbf{B_{BTI_{LW,i}}} = \frac{(\mathrm{EC_{W,i}} - [\frac{\mathrm{EC_{W-1,i}} + \mathrm{EC_{W-2,i}}}{2}]}{(\mathrm{EC_{W-1,i}} + \mathrm{EC_{W-2,i}})/2} * 100$$ $$\mathbf{B_{BTI_{LW,M}}} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}} \mathrm{B_{BTI_{LW,i}}}$$ BBTILY,i = Building "i" comparison with two last weeks (with itself) ECw,i = Energy Consumption in the time range for building "i" ECW-1,i , ECW-2,i = Energy Consumption of the two previous weeks for building "i" N = number of buildings utilized for the KPI calculation		
Calculating frequency	Weekly		
Calculation Methodology			
Step	**Description**		
01	The calculation takes into account: 2.1.1. The time range (reference week) 2.1.2. The time range for benchmark (the two previous weeks) 2.1.3. The building 2.1.4. The perimeter of the analysis: Total energy consumption, or, where available the energy consumption of heating or cooling, lighting		

02	The formula will be applied for each one of the selected buildings, then arithmetic mean will be calculated from these selected values.			
03	Normalize both the consumptions by the comfort level (where available) Comfort level is a range of internal temperature and humidity that must be complied Comfort level = f(internal temperature, internal humidity) (Internal humidity, internal temperature) = f (external humidity, external temperature)			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Office Registry	Building Data	At starting up and then occasionally, when changes occur	No Temporal Range	Poste Italiane
Building Calendar	Building Data	Monthly	From 01/01/2018	Poste Italiane
Detailed Energy Consumption	Energy Consumption	Daily	From 01/01/2018	Poste Italiane
Detailed Energy Consumption DL_102	Energy Consumption	Monthly	TBD	Poste Italiane
Total Active Energy consumption	Energy Consumption	Monthly	From 01/01/2018	Poste Italiane
Temperature, Humidity	Weather			External Services

KPI N°4			
KPI-Name	Building Benchmarking BtB	**KPI-ID**	PI_KPI04
KPI-Type	Business		
Description	The KPI calculate, in % value, the difference in Energy consumption between a cluster of buildings.		
Target Value	+-10%	**Threshold Value**	+-20%
Rounding	round off to 0% for values between 0.00 and 0.49 and to 1% for values above		
Unit	Kilowatt per hour (KWh)		
Formula			

	$$\mathbf{B_{BTB,i}} = \frac{\frac{B_i}{m_i^3} - (\sum_j \frac{B_j}{m_j^3})/(n-1)}{(\sum_j \frac{B_j}{m_j^3})/(n-1)} * 100$$ $$\mathbf{B_{BTB,M}} = \frac{1}{N}\sum_i B_{BTB,i}$$ $B_{BTB,i}$ = Building Energy Consumption comparison with the mean of the same cluster B_i = Energy Consumption of Building "i" B_j = = Energy Consumption of Building "j" (Some cluster of "i", i.e., some typology and destination use) n = number of buildings in the cluster m^3 = volume of building N = number of buildings utilized for the KPI calculation
Calculating frequency	Weekly (Alert if Threshold Value is exceeded)
Calculation Methodology	
Step	**Description**
01	The calculation takes into account: 1. The time range (current year last week) 2. The building types 3. The building's destination uses 4. the perimeter of the analysis: Total energy consumption or, where available the energy consumption of heating or cooling, lighting
02	The formula will be applied for each one of the selected buildings, then arithmetic mean will be calculated from these selected values.
03	Normalize the consumptions of both the buildings by the comfort level (where available). Comfort level* is a range of internal temperature and humidity that must be complied. *Comfort level = f(internal temperature, internal humidity) (Internal humidity, internal temperature) = f(external humidity, external temperature)

Data Source

Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Office Registry	Building Data	At starting up and then occasionally, when changes occur	No Temporal Range	Poste Italiane
Building Calendar	Building Data	Monthly	From 01/01/2018	Poste Italiane
Detailed Energy Consumption	Energy Consumption	Daily	From 01/01/2018	Poste Italiane

Detailed Energy Consumption DL_102	Energy Consumption	Monthly	TBD	Poste Italiane
Total Active Energy consumption	Energy Consumption	Monthly	From 01/01/2018	Poste Italiane
Temperature, Humidity	Weather		From 01/01/2018	External Services

KPI N°5			
KPI-Name	CO2 emission reduction	**KPI-ID**	PI_KPI05
KPI-Type	Business		
Description	The KPI calculate the impact of energy consumption reduction on CO2 emissions in a time range		
Target Value	≥ 10%	**Threshold Value**	0≤ $\Delta(\mathbf{CO_2})_{\mathrm{y,M}}$ <10%
Rounding	round off to 0 for values between 0.00 and 0.49 and to 1 for values above		
Unit	Kg		
Formula	$\Delta(\mathbf{KWh})_{\mathrm{y,i}} = \frac{\mathrm{Budget\ (Kwh)_{y,i}} - \mathrm{Consumption\ (Kwh)_{y,i}}}{\mathrm{Consumption\ (Kwh)_{y,i}}} * 100$ $\Delta(\mathbf{KWh})_{\mathrm{y,i}} = \Delta(\mathbf{CO_2})_{\mathrm{y,i}}$ Because $\mathrm{C_{O2}\ (Kg)} = 0{,}36099 * \mathrm{Energy\ (KWh)}$ Finally $\Delta(\mathbf{CO_2})_{\mathrm{y,M}} = \frac{1}{\mathrm{M}} \sum_{\mathrm{i}} \Delta(\mathrm{CO_2})_{\mathrm{y,i}}$ Budget (kWh)y,i = yearly budget of building “i” Consumption (kWh)y,I = yearly consumption of building “i” Δ(KWh) y,i = consumption saving percentage of building “i” Δ (CO_2) y,I = CO_2 saving percentage of building “i” M = number of buildings utilized for the KPI calculation		
Calculating frequency	Yearly		

Calculation Methodology				
Step	**Description**			
01	Calculate the yearly total consumption of the building			
02	The formula will be applied for each one of the selected buildings, then arithmetic mean will be calculated from these selected values.			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Office Registry	Building Data	At starting up and then occasionally, when changes occur	Static - No Temporal Range	Poste Italiane
Building Calendar	Building Data	Monthly	From 01/01/2018	Poste Italiane
Total Active Energy consumption	Energy Consumption	Monthly	From 01/01/2018	Poste Italiane

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KPI N°6			
KPI-Name	Recall	**KPI-ID**	PI_KPI06
KPI-Type	Technical		
Description	The KPI measures the number of cases which correctly classified as problematic (True Positives) by the algorithm divided by the sum of the cases that were classified as normal but actually were problematic (False Positives) plus the number of True Positives.		
Target Value	90%	**Threshold Value**	>=80%
Rounding	N/A		
Unit	Adimensional		
Formula	$Recall = \frac{TruePositives}{TruePositives + FalsePositives}$		

Calculating frequency	Monthly			
Calculation Methodology				
Step	**Description**			
01	The time range comprises the historical data up to the month chosen for the analysis			
02	2.5.3. Identify all those cases where correctly identified (TruePositives) as abnormalities in the Heating and Cooling system and those which are classified as normal but are cases with anomalous behaviors (False Negatives).			
03	Apply the formula			
04	The formula will be applied for each one of the selected buildings.			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Office Registry	Building Data	At starting up and then occasionally, when changes occur	Static - No Temporal Range	Poste Italiane
Building Calendar	Building Data	Monthly	From 01/01/2018	Poste Italiane
Detailed Energy Consumption	Energy Consumption	Daily	From 01/01/2018	Poste Italiane
Alarms of abnormal behaviours of the systems	System Fault	Daily	From June 2021	Poste Italiane
Temperature, Humidity	Weather		From 01/01/2018	External Services
Systems Registry	Building Systems	At starting up and then occasionally, when changes occur	No Temporal Range	Poste Italiane

KPI N°7			
KPI-Name	Precision	**KPI-ID**	PI_KPI07
KPI-Type	Technical		
Description	The KPI measures Pre-MATE's performance. Precision, is defined as the ratio of all cases that are correctly identified as problematic (True Positives) to all cases that are identified as problematic, even if they are not, actually (All Positives-True and False).		
Target Value	90%	**Threshold Value**	>=80%

Rounding	N/A			
Unit	Adimensional			
Formula	$Precision = \frac{TruePositives}{TruePosives + FalsePositives}$			
Calculating frequency	Monthly			
Calculation Methodology				
Step	**Description**			
01	The time range comprises the historical data up to the month chosen for the analysis			
02	Identify all those cases where correctly identified (True Positives) as abnormalities in the Heating and Cooling system and those which are classified as problematic but are actually normal behaviors (False Negatives)			
03	Apply the formula			
04	The formula will be applied for each one of the selected buildings.			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Office Registry	Building Data	At starting up and then occasionally, when changes occur	No Temporal Range	Poste Italiane
Building Calendar	Building Data	Monthly	From 01/01/2018	Poste Italiane
Detailed Energy Consumption	Energy Consumption	Daily	From 01/01/2018	Poste Italiane
Alarms of abnormal behaviours of the systems	Systems Fault	Daily	From June 2021	Poste Italiane
Temperature, Humidity	Weather		From 01/01/2018	External Services
Systems Registry	Building Systems	At starting up and then occasionally when changes occur	No Temporal Range	Poste Italiane

KPI N°8				
KPI-Name	F1-Score		**KPI-ID**	PI_KPI08
KPI-Type	Technical			
Description	The KPI is used in cases where the best combination of precision and recall is desired. F_1 score could be used to combine the two criteria. The F_1 score is the harmonic mean of precision and recall, using the formula below to account for both metrics			
Target Value	90%	**Threshold Value**	>=80%	
Rounding	N/A			
Unit	Adimensional			
Formula	$$F_1 = 2\frac{Precision \cdot Recall}{Precision + Recall}$$			
Calculating frequency	Bi-Monthly			
Calculation Methodology				
Step	**Description**			
01	The time range comprises the historical data up to the month chosen for the analysis			
02	Calculate Recall and Precision KPIs before			
03	Apply the formula			
04	The formula will be applied for each one of the selected buildings			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Office Registry	Building Data	At starting up and then occasionally when changes occur	No Temporal Range	Poste Italiane

Building Calendar	Building Data	Monthly	From 01/01/2018	Poste Italiane
Detailed Energy Consumption	Energy Consumption	Daily	From 01/01/2018	Poste Italiane
System Registry	Building Systems	At starting up and then occasionally, when changes occur	No Temporal Range	Poste Italiane
Employees Number	Occupancy	Monthly	From 01/01/2018	Poste Italiane

KPI N°09			
KPI-Name	Performances Analysis	**KPI-ID**	PI_KPI09
KPI-Type	Technical/Business		
Description	This KPI measures the energy consumed by the conditioning systems for returning to optimal internal temperature, normalized for the temperature recover range.		
Target Value	5% (month to month increase)	**Threshold Value**	10% (month to month increase)
Rounding	No		
Unit	KWh		
Formula			

$$\mathbf{E_{cond,k}} = \frac{1}{M - N + 1}\sum_{j=N}^{M}\frac{(\bar{E}_{cons,k,j} - E_{bias,k})}{|T_{thr} - T_{int,k}| \times volume \times p_j}$$

$$where$$

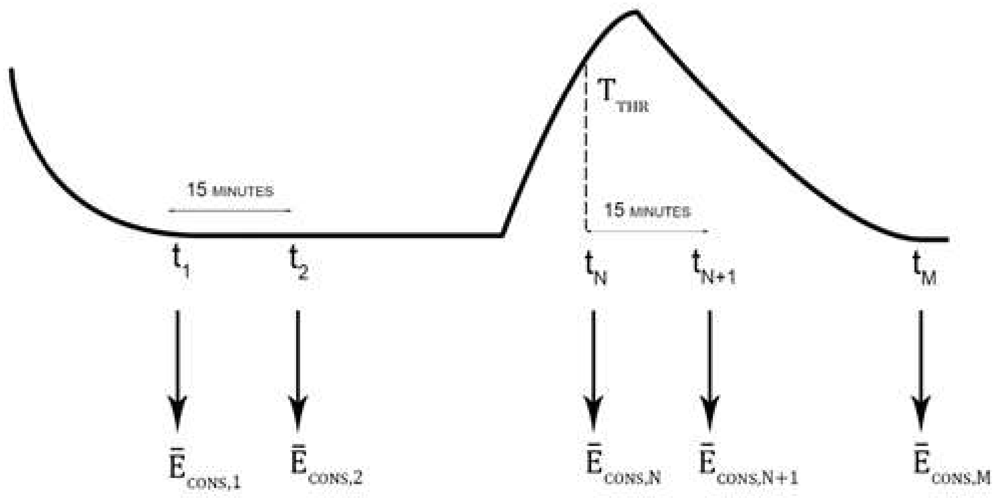
$$\mathbf{E_{bias,k}} = \frac{1}{N}\sum_{n=1}^{N}\bar{E}_{cons,n}$$

$$\mathbf{p_j} = \frac{\#\ of\ sensor\ out\ of\ range, at\ the\ time\ 'j'}{total\ number\ of\ sensors\ in\ the\ building}$$

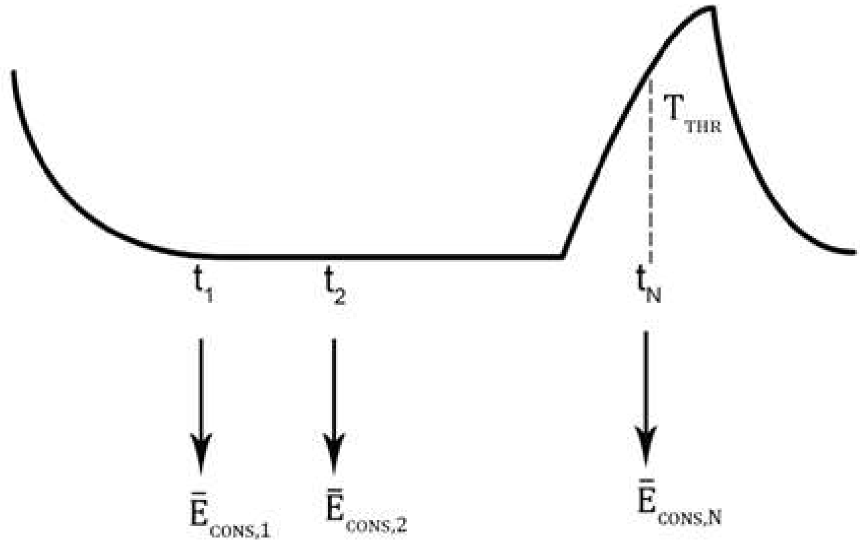
$$finally$$

$$\mathbf{E_{cond1\_m}} = \frac{1}{K}\sum_{k}\mathbf{E_{cond,k1\_m}}$$

= normalized energy the conditioning systems consume per unit of volume and temperature to bring the internal temperature back to the normal range, for the temperature violation 'k'. (is costituited by M-N+1 fifteen minutes interval see figure below)



= energy consumed for conditioning in the optimal range of temperature (from t_1 to t_2) and till the threshold reached(from t_2 to t_N), when is on range or above (see figure below)

	(19° or above in the heating tabulated period, 27° or below in the cooling tabulated period), for the temperature violation 'k')  when is on range or above (19° or above in the heating tabulated period, 27° or below in the cooling tabulated period), for the temperature violation 'k') = Energy consumption at time 'j' = temperatute threshold : they are tabulated : 19° (in the heating tabulated period) ; 27° (in the cooling tabulated period) = max out of range internal temperature to recover for the temperature violation 'k' volume= building volume = normalized energy the conditioning systems consume per unit of volume and temperature to bring the internal temperature back to the normal range, for the month 'm' and the building 'i' K = number of violations for the month 'm' and the building 'i' = ratio between the number of sensor out of range at the time 'j and the total number of sensors in the building
Calculating frequency	Monthly
Calculation Methodology	
Step	**Description**
01	Data have to be taken on building type = Smart building, in the total time window of availability of data. Data must be considered only for days and hours in which the buildings are open
03	Calculate the plants consumption taking into account, for each temperature violation, the energy consumed for the conditioning, normalized by bias energy, temperature interval, and number of sensors outside range in that moment
04	Apply the formulas. We will have a value for each smart building and for each month, so could be compared the performance of different months of the same building for degradation analysis or could be compared performance of different buildings (in which case will be useful compare the same month)
Data Source	

Data description	Data source	Data collection frequency	Data collection time range	Data Owner
Office Registry	Building Data	At starting up and then occasionally, when changes occur	Static - No Temporal Range	Poste Italiane
Building Calendar	Building Data	Monthly	From 01/01/2018	Poste Italiane
Detailed Energy Consumption	Energy Consumption (and internal temperatures)	Daily	From when they are available	Poste Italiane

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KPI N°10			
KPI-Name	Lighting Estimation	**KPI-ID**	PI_KPI10
KPI-Type	Technical		
Description	The KPI calculates the % of deviation between the actual and the estimated lighting consumption.		
Target Value	+/- 5%	**Threshold Value**	+/- 10%
Rounding	round off to 0% for values between 0.00 and 0.49 and to 1% for values above		
Unit	Kilowatt per hour (KWh)		
Formula	$$\mathbf{LE_i} = \frac{L_{e,i} - L_{a,i}}{L_{a,i}} * 100$$ $$\mathbf{LE_M} = \frac{1}{N}\sum_i LE_i$$ LE_i = Lighting Estimation Error % of building "I" L_e = Lighting consumption estimated of building "I" L_a = Lighting consumption actual of building "I" N = number of buildings utilized for the KPI calculation		

Calculating frequency	Weekly
Calculation Methodology	
Step	**Description**
01	Select the time range and the building (month)
02	Calculate the estimated consumption considering the following information: 1. Total energy consumption in the rime range 2. Parameter on % of incidence of consumption form Heating and Cooling systems 3. Building open hours and shift
03	Lighting consumption estimation will be compared to the real consumption (where available) and then will be exploited by buildings for which is no available.
03	Calculate the real consumption value
04	Apply the formula
05	The formula will be applied for each one of the selected buildings, then arithmetic mean will be calculated from these selected values.

Data Source

Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Office Registry	Building Data	At starting up and then occasionally when changes occur	No Temporal Range	Poste Italiane
Building Calendar	Building Data	Monthly	From 01/01/2018	Poste Italiane
Detailed Energy Consumption	Energy Consumption	Daily	From 01/01/2018	Poste Italiane
Detailed Energy Consumption DL_102	Energy Consumption	Monthly	TBD	Poste Italiane
Total Active Energy consumption	Energy Consumption	Monthly		Poste Italiane
System Registry	Building Systems	At starting up and then occasionally, when changes occur	No Temporal Range	Poste Italiane

Employees Number	Occupancy	Monthly	From 01/01/2018	Poste Italiane

Pilot 3b – ROM Advanced Energy Management System and Spatial (Multi-Scale) Predictive Models in the Smart City

Pilot 3b – ROM Advanced Energy Management System and Spatial (Multi-Scale) Predictive Models in the Smart City

<table>
<tr><td colspan="5">KPI N°01</td></tr>
<tr><td>KPI-Name</td><td colspan="2">Total Energy Savings (TES)

[kWh / Y]

Derived: Total Energy Cost Savings (TECS)</td><td>KPI-ID</td><td>ROM_Kpi_R01a

ROM_Kpi_R01b</td></tr>
<tr><td>KPI-Type</td><td colspan="4">Technical - <u>Energy Savings</u> and <u>Energy Cost Savings</u></td></tr>
<tr><td>Description</td><td colspan="4">The analysis and the improved management of the meters data (historical and current) will produce a series of measures and interventions (“EVENTS”) that should reduce the yearly total energy consumptions, such as dismission of un-useful meters, maintenance and interventions on buildings following some anomalies detection, contractual re-definition resulting from Platoon analysis, other measures impacting on behaviours.

Component indicators are the <u>Total Energy Savings</u> in terms of Gas (TES-G) and in terms of Electricity (TES-E), that gives a better picture of the impact of Platoon services.

TeS can be applied also to different reference or analysis period different from Year.

This KPI calculates for example the difference between the energy consumption before and after reference EVENTS.

It is always necessary to explicit the subset of buildings refereed to an instance calculation. This subset can range from n.1 meter/building to all meters/buildings</td></tr>
<tr><td>Target Value</td><td>1 % =relevant;
2 % =good;
3 % =very good;
Over 3% =excellent</td><td>Threshold Value</td><td colspan="2">1 %</td></tr>
<tr><td>Rounding</td><td colspan="4">---%

round off to 0% for values between 0.00 and 0.49 and to 1% for values above</td></tr>
<tr><td>Unit</td><td colspan="4">[Kilowatt (KWh) / year] for TES ; [Euro /year] for TECS</td></tr>
</table>

Formula	**$TES_Y = TES_G + TES_E$** $TES_{AY} = \frac{TES_A}{\text{Ref.period}} = \frac{TES_E + TES_G}{\text{Ref. period}}$ TESY = Total Energy Saving (for one full year) TES_F = Forecasted value (calculated for 1 full year after the event, including future periods) TES_{AY} = Actual value normalized on 1 full year TES_A = Actual value (sum of the measured savings from the EVENT time to last data available, when total period is different from 1 year) EVENT time = the date of the intervention / action / event
Calculating frequency	On demand … Monthly
Calculation Methodology	
Step	**Description**
01	Select the time range = Ref. Period (year) ; default is 1 (year) I.e 1 month = 1/12; 18 months = 18/12 Select/identify/Set the EVENT time, in order to verify which period covered by data is available after this EVENT time. Ref.Period is set to this period
02	Select the specific building(s) and the perimeter of calculation: Total energy consumption for District / Area buildings or Total energy consumption for Specific building(s)
03	Select the Energy typology: Electric (power meters) or Gas (gas meters or kWh derived from contatermie dataset) Or Both

04	Calculate energy saving for selected typology/building(s) comparing consumption related to one full year before the EVENT (ECb) and consumptions after the EVENT (ECa) (normalized if necessary to one full year) : ECa – ECb = TES			
05	Calculate % as TES / ECb *Note: repeat for TECS using Euro instead of kWh*			
Data Source				
Data description	**Data source**	**Data collection frequency**	**Data collection time range**	**Data Owner**
Building Calendar	Building Data	Monthly	TBD	
Total Electric Energy consumption	Energy Consumption	Monthly	TBD	ROM
Total Gas Energy consumption	Energy Consumption	Monthly	TBD	ROM
Detailed Energy Consumption	Energy Consumption (electric or gas)	Monthly (daily if using connectors)	TBD	ROM
Detailed Energy Costs	Energy Costs (electric or gas)	Monthly (daily if using connectors)	TBD	ROM

KPI N°02			
KPI-Name	Saving Personnel Costs Saving Other Costs	**KPI-ID**	**ROM_Kpi_R02a** **ROM_Kpi_R02b**
KPI-Type	Technical		
Description	The installation of a monitoring system shall reduce the costs for the personnel. This KPI-02a is calculated from the difference of the saved personnel costs (per year) and the depreciation amount of the data monitoring system. The KPI-02b is calculated listing other (than KPI02a) costs saved through the use of Platoon toolbox. Kpi_R02a and Kpi_R02b can be summed. Both exclude costs saving derived by the Direct Energy Saving		
Target Value	20%	**Threshold Value**	15%
Unit	% on Euro [per year]		

Formula	$$SPC = \frac{(CS - CD)}{C_A} \times 100$$ CS= Personnel cost saving, based on the calculation of the avoided yearly worked days CD = depreciation amount of the data monitoring system in the same year C_A = Actual value of the personnel cost for the specific functions and tasks covered by toolbox (before Platoon implementation) Note: the calculation has to be extended to the personnel directly involved or impacted indirectly by the toolbox usage.
Calculating frequency	Monthly

KPI N°03			
KPI-Name	Nb of Meters with Energy Savings Results (Nb of Meters)	**KPI-ID**	ROM_Kpi_R03
KPI-Type	Technical - Energy Savings and Counting Interventions		
Description	This indicator counts the number of energy meters for which PLATOON data analytics tools produce some action resulting in energy saving during the year. Another Derived KPI: KPI01/KPI03 represents the average energy saved per meters involved, and measures the average intensity of the single EE intervention or result		
Target Value	Non relevant <1 Up to 10 =relevant; 11-30 =good;	**Threshold Value**	>10 =good;
Unit	Natural Number		
Formula	Counting occurences		
Calculating frequency	On demand … Monthly		

Calculation Methodology	
Step	**Description**
01	Select the time range = Ref. Period (year) ; default is 1 (year) I.e 1 month = 1/12; 18 months = 18/12 Select/identify/Set the EVENT time, in order to verify which period covered by data is available after this EVENT time. Ref.Period is set to this period
02	Select the specific building(s) and the perimeter of calculation: Total meters for District / Area buildings or Total meters for Specific building(s) It is always necessary to explicit the subset of buildings refereed to an instance calculation. This subset can range from n.1 energy meter to all meters (all buildings)
03	Select the Energy typology: Electric (power meters) or Gas (gas meters or kWh derived from contatermie dataset) Or Both
04	Calculate the number of meters, in the above defined perimeters or set, that produced an energy saving output to be considered as a toolbox result. repeat for different energy typology if requested

KPI N°04			
KPI-Name	Nb of Anomalies detected	**KPI-ID**	**ROM_Kpi_R04**
KPI-Type	Technical - Economical		
Description	The definition of Anomaly for a specific energy meter is based on the occurrence of the consumption divergence from the expected value (benchmark analysis), in the same period. This divergence could concern the EC (but could be applied also to the EP or to the Costs).		

	The Divergence is determined by the users when defining the specific rule-set for the indicator.		
Target Value	10 =relevant; 11-20 =good;	**Threshold Value**	>10
Unit	Natural Number		
Formula	counting of the occurrence		
Calculating frequency	Monthly		

KPI N°05			
KPI-Name	CO2 emission reduction	**KPI-ID**	**ROM_Kpi_R05**
KPI-Type	Technical		
Description	The avoided CO2 emission corresponding to the results in terms of Energy Savings (KPI-01) deriving from or correlated to the use of Platoon Toolbox		
Target Value	Same of KPI-01	**Threshold Value**	Same of KPI-01
Unit	gCO2 (divide per 1.000.000 for TonsCO2)		
Formula	Same Formula and calculation used for KPI-01 then Multiply kWh obtained per 258,63 for gCO2 (divide per 1.000.000 for TonsCO2) NOTE: Conversion Factor for Italy- Rome & Power Energy (258,63 g CO2/kWh) For Gas consumptions savings use Conversion Factors defined by ISPRA at current date		
Calculating frequency	Monthly		

KPI N°06			
KPI-Name	RES suggested self-consumptions RES potential production (REC)	**KPI-ID**	**ROM_Kpi_R06a** **ROM_Kpi_R06b**
KPI-Type	Technical		

Description	Suggested self-consumptions energy for optimized PV plant installable on roofs Or maximum RES production that can be installed on the roof when planning a PV plant within the REC (Energy Communities) scheme, where also the exceeding energy is shared with other proximity meters.		
Target Value	Over 130.000 =relevant; Up to 400.000 =good; Up to 800.000 =very good; over 1.200.000 =excellent	**Threshold Value**	>400.000
Unit	(kWh/years)		
Formula	Pv Potentialities service (S04) offers a series of output, for each building with PV plants, based on the load curves (updated periodically), on the availability of irradiated surfaces to install more PV modules, their tilt/orientation, BOD (using PV-GIS JRC model). It includes the calculation of (A) the self-consumption energy component **ROM_Kpi_R06a** And (B) The maximum RES production **ROM_Kpi_R06b** Sum (A) or (B) for all the buildings analyzed. It is possible to limit the analysis to a district perimeter or to a subset of public building on the choice of the operator.		
Calculating frequency	On Demand or Monthly		

KPI N°07			
KPI-Name	Nb of Tools Outputs or occurrences from Toolbox log	**KPI-ID**	**ROM_Kpi_R07**
KPI-Type	Technical - Behavioral		
Description	Number of Queries or Actions with Output processed by the Toolbox. Measuring the usage, this KPI is referring about the effective engagement of the ROM personnel. Counting outputs for each distinct services and tools will help to address further development and exploitation strategies.		
Target Value	Over 100 =relevant; over 200 =good;	**Threshold Value**	>200

	over 400 =very good; over 600 =excellent		
Unit	Natural Number		
Formula	counting of the occurrence for a period or 1 year Calculated counting the outputs coming from the Platoon Toolbox for Pilot-3b-ROM during the user test phase (12 months). Extracted from Toolbox internal log. Can be limited to one specific service or to the whole toolbox.		
Calculating frequency	Monthly or Yearly		

KPI N°08			
KPI-Name	Nb of Tools Outputs or occurrences from Toolbox log	**KPI-ID**	**ROM_Kpi_R08**
KPI-Type	Technical - Behavioral		
Description	Vote assigned by the Test Users as a rating for each Services. It is Calculated at the end of the final User Test phase, where 10 Officers assigned a vote for each services a for each of the 7 assessment criteria It can be recalculated each time a group of users or potential users intends to rate the services. The Questionnaire presenting the 7 rating criteria is accompanied also by few questions for free answers focusing on priority improvements that could turn the services more suitable with their work and expectations		
Target Value	Target: >6	**Threshold Value**	>5
Unit	Natural Number - Range [0 – 10]		
Formula	for each of the 5 Services (S01, S02, S03, S04 and the Association Section of the toolbox) There are 7 assessment criteria to rate separately: Layout, Intuitive use or usability, Usefulness, Use Frequency estimated, Workflow improvement, Impact on optimization of their task, Impact on Energy Efficiency		
Calculating frequency	Monthly or Yearly		

Pilot 3C Energy Efficiency and Predictive Maintenance in the Smart Tertiary Building Hub Grade

LLUC-3C-01

KPI N°1				
KPI-Name	Integration		**KPI-ID**	2
KPI-Type	Technical			
Description	Metric targeted at the validation of the fact that the tools of this pilot are able to work together. This includes: -Semantic pipeline: PLATOON data models mapping -Data Connectors with legacy databases, sensors, edge computing devices -IDS connector between Giroa and Tecnalia -IDS connector with Broker and Marketplace -Data Analytics Tools			
Target Value	1	**Threshold Value**	1	
Rounding	Not applicable			
Unit	Binary 1 or 0			
Formula	If all tools to complete the pilot data analysis are able to interact and send data to each other then this KPI is 1. Otherwise it is 0.			
Calculating frequency	At each pipeline release			
Calculation Methodology				
Step	**Description**			
01-	based on unit tests the input-output functioning of each pipeline is validated.			
02	Test data is exchanged between the pilot analytics blocks			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Test data	Energy consumption/generation data, energy price data, meteo data and operational parameters.	Mins	2021-2022	Giroa

KPI N°2

KPI-Name	Energy Bill reduction		**KPI-ID**	2
KPI-Type	Business			
Description	The KPI will evaluate the energy bill reduction achieved			
Target Value	20% reduction	**Threshold Value**	All improvement compared to current situation is already useful.	
Rounding	first decimal			
Unit	% and euros			
Formula	(Current energy bill (euros)- New energy bill(euros))/ Current energy bill (euros)			
Calculating frequency	Once per day			
Calculation Methodology				
Step	**Description**			
01-	Calculate the energy generation and consumption forecast			
02	Calculate corrected energy price taking into account energy production excess and selling/buying poll pricre			
03	Optimise HVAC on/off			
04	Calculate HVAC energy consumption			
05	Calculate energy bill taking into account outputs from steps 2 and 4.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Test data	Energy consumption/generation data, energy price data, meteo data and operational parameters.	Mins	2021-2022	Giroa

KPI N°3			
KPI-Name	RES utilization ratio	**KPI-ID**	3
KPI-Type	Technical		

Description	The KPI will evaluate the RES usage versus overall energy consumption.			
Target Value	30% increase		**Threshold Value**	Full processing chain for a farm should be able to run on a standard server.
Rounding	1st decimal			
Unit	Percentage			
Formula	RES production usage/ overall energy consumption			
Calculating frequency	Once per day			
Calculation Methodology				
Step	**Description**			
01-	Calculate the energy generation and consumption forecast			
02	Calculate corrected energy price taking into account energy production excess and selling/buying poll pricre			
03	Optimise HVAC on/off			
04	Calculate HVAC energy consumption			
05	Calculate RES usage taking into account outputs from steps 1 and 4.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Test data	Energy consumption/generation data, energy price data, meteo data and operational parameters.	Mins	2021-2022	Giroa

LLUC-3C-02

KPI N°1			
KPI-Name	Health Monitoring	**KPI-ID**	KPI-01
Description	Monitoring the health status of each asset, using the PML (Process Mastery Level) indicator, in a range from 0 (Failure Status) to 1 (Optimal Status).		

<table>
<tr><td></td><td colspan="4"></td></tr>
<tr><td>Target Value</td><td>100 %</td><td>Threshold Value</td><td colspan="2">0 – 100%</td></tr>
<tr><td>Unit</td><td colspan="4">Percentage indicator, set points, etc.</td></tr>
<tr><td>Formula</td><td colspan="4">Each defined failure mode will have specific Digital twin based on machine learning algorithms. From those models, the real time information grouped by time slots (for example, 8 hours) will be evaluated against the Digital twin.
Statistics for the digital twin testing:
R^2
MAE

The correlation will be evaluated in a range from 0 to 1 as a FTL

Always depending on the availability of signals, an attempt will be made to extract information about the following PMLs:
Energy Variator
Starter
Phase imbalance
Power Supply
Communications
Flow Meter
Temp Out of range
Evaporator Return
Temp Increase
Power consumption increase
Evaporator Outlet Temp</td></tr>
<tr><td>Calculating frequency</td><td colspan="4">Depending on the asset. From 4 to 24 hours</td></tr>
<tr><td colspan="5">Calculation Methodology</td></tr>
<tr><td>Step</td><td colspan="4">Description</td></tr>
<tr><td>01-</td><td colspan="4">Define the PML Formula for each asset</td></tr>
<tr><td>02-</td><td colspan="4">Monitoring the health status according to the values of the variables and its associated PML Value.</td></tr>
<tr><td colspan="5">Data Source</td></tr>
<tr><td>Data description</td><td>Data source</td><td>Data collection frequency</td><td>Data collection time range</td><td>Data Owner</td></tr>
<tr><td>Signals used as input for the models</td><td>Consolidated Data Base with PLC and SCADA data</td><td>Defined default time (every 15 min aprox.)</td><td></td><td>GIROA</td></tr>
</table>

KPI N°2				
KPI-Name	Availability		**KPI-ID**	KPI-02
Description	Availability of the asset over a period of time. Availability takes into account Availability Loss, which includes any events that stop planned production for an appreciable length of time (usually several minutes; long enough for an operator to log a reason). Used for OEE calculation.			
Unit	%			
Formula				
Calculating frequency	Daily			
Calculation Methodology				
Step	**Description**			
01-	Register events of unplanned stops.			
02	Calculate the availability for a determined period of time by using the above formula.			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Signals used as input for the models	Consolidated Data Base with PLC and SCADA data	Defined default time (every 15 min aprox.)		GIROA

KPI N°3			
KPI-Name	Mean Time Between Failures	**KPI-ID**	KPI-03
Description	Mean time between failures (MTBF) describes the expected time between two failures for a repairable system		
Unit	Hours		
Formula	MTBF = (Total Working Time – Total Breakdown Time) / Number of Breakdowns MTBF = Total Operational time / Number of Breakdowns		
Calculating frequency	Daily		
Calculation Methodology			
Step	**Description**		
01-	Acquire running operational time		

02-	Determine Number of breakdowns. Apply filters as needed to exclude micro stops, mini stops, or other criteria's			
03-	Apply formula			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Signals used as input for the models	Consolidated Data Base with PLC and SCADA data	Defined default time (every 15 min aprox.)		GIROA

KPI N°4			
KPI-Name	Maintenance Costs	**KPI-ID**	KPI-04
KPI-Type	Business		
Description	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.		
Target Value	Not applicable	**Threshold Value**	Not applicable
Rounding	Not applicable		
Unit	Euros		
Formula	Sum of the maintenance costs of the equipment selected for the use case.		
Calculating frequency	Daily		
Calculation Methodology			
Step	**Description**		
01-	Acquire necessary data from integration with Prisma (CMMS) Total cost associated to Work Orders related to the equipment		
02	Create total cost KPI associated to the equipment		

Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Test data	Operational parameters.	Mins	2021-2022	Giroa

Maintenance log data	Prisma	Daily	Daily	Giroa

KPI N°5			
KPI-Name	Integration	**KPI-ID**	KPI-05
KPI-Type	Technical		
Description	Metric targeted at the validation of the fact that the tools of this pilot are able to work together. This includes: -Semantic pipeline: PLATOON data models mapping -Data Connectors with legacy databases, sensors, edge computing devices -IDS connector between Sisteplant and Tecnalia -IDS connector with Broker and Marketplace -Data Analytics Tools		
Target Value	1	**Threshold Value**	1
Rounding	Not applicable		
Unit	Binary 1 or 0		
Formula	If all tools to complete the pilot data analysis are able to interact and send data to each other then this KPI is 1. Otherwise it is 0.		
Calculating frequency	At each pipeline release		
Calculation Methodology			
Step	**Description**		
01-	based on unit tests the input-output functioning of each pipeline is validated.		
02	Test data is exchanged between the pilot analytics blocks		

Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Test data	Energy consumption/generation data, energy price data, meteo data and operational parameters.	Mins	2021-2022	Giroa

Pilot 4a Energy Management of Microgrids

LLUC P-4a-01

KPI N°1				
KPI-Name	Energy availability	**KPI-ID**	KPI-1	
KPI-Type	Technical (specific to the pilot use case)			
Description	Optimal energy consumption (increase in energy availability) – Optimization for renewable electricity generation Smart storage/generation			
Target Value	Example: amount of daily load covered by renewable generation – Target value:100%	**Threshold Value**	The value used to assess the effectiveness/efficiency performance of the monitored process: 90%	
Rounding	the criteria for rounding the calculated values (Example : For % calculation, round off to 0% for values between 0.00 and 0.49 and to 1% for values above)			
Unit	%			
Formula	$$\mathrm{KPI}_{01}(\%) = \frac{\sum_{t=1}^{N} P_{PV,t}}{\max\left(\sum_{t=1}^{N} P_{PV,t}, \sum_{t=1}^{N} P_{load,t}\right)} \cdot 100$$			
Calculating frequency	Daily			
Calculation Methodology				
Step	**Description**			
01-	Daily measurements of load consumption, renewable energy generation and battery			
02				
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Energy consumption	mySQL db	10 min	daily	PDM
Energy production	mySQL db	10 min	daily	PDM

KPI N°2

KPI-Name	Cost			**KPI-ID**	KPI-2
KPI-Type	Technical (specific to the pilot use case)				
Description	Reduction of maintenance effort and costs (optimization for renewable electricity generation)				
Target Value	Example: maintenance cost		**Threshold Value**		10%
Rounding	the criteria for rounding the calculated values (Example : For % calculation, round off to 0% for values between 0.00 and 0.49 and to 1% for values above)				
Unit	%				
Formula	$\mathrm{KPI}_{02}(\%) = \frac{\sum_{t=1}^{N}\left(P_{load,t} - P_{PV,t}\right)}{\sum_{t=1}^{N} P_{load,t}} \cdot 100$				
Calculating frequency	daily, montly				
Calculation Methodology					
Step	**Description**				
01-	Daily measurements of load consumption, renewable energy generation and battery				
02					
Data Source					
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner	
Failure rate	mySQL db	10 min	daily	PDM	
Maintenance activity	mySQL db	10 min	daily	PDM	

KPI N°3			
KPI-Name	Forecast accuracy	**KPI-ID**	KPI-3
KPI-Type	Technical (specific to the pilot use case)		
Description	Reduced forecasting errors (generation and load forecast)		
Target Value	Example: forecating error – Target value:0%	**Threshold Value**	The value used to assess the effectiveness/efficiency performance of the monitored process: 20%

Rounding	None			
Unit	%			
Formula	Standard forecating error indicators, such as nRMSE, WMAE, EMAE, OMAE $$\mathrm{KPI}_{03}(\%) = \mathrm{nRMSE} = \frac{1}{\max\,(P_{m,t})}\sqrt{\frac{\sum_{t=1}^{N}\left(P_{f,t} - P_{m,t}\right)^2}{N}} \cdot 100$$ $$\mathrm{EMAE} = \frac{\sum_{t=1}^{N}\left|P_{f,t} - P_{m,t}\right|}{\sum_{t=1}^{N}\max\left(P_{f,t}, P_{m,t}\right)} \cdot 100$$ [S. Leva, M. Mussetta, A. Nespoli and E. Ogliari, "PV power forecasting improvement by means of a selective ensemble approach," 2019 IEEE Milan PowerTech, 2019, pp. 1-5, doi: 10.1109/PTC.2019.8810921.]			
Calculating frequency	Daily, monthly, yearly			
Calculation Methodology				
Step	**Description**			
01-	Daily measurements of renewable energy generation			
02	Comparison with related forecasting and error measurement			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Energy consumption	mySQL db	10 min	daily	PDM
Energy production	mySQL db	10 min	daily	PDM
Production forecast	mySQL db	10 min	daily	PDM
Solar nowcast	mySQL db / edge node?	10 min	daily	PDM
Load forecast	mySQL db	10 min	daily	PDM

KPI N°4			
KPI-Name	Realtime	**KPI-ID**	KPI-4

KPI-Type	Technical (specific to the pilot use case)			
Description	Ability to monitoring/analyze/optimize data and the system at real time rate (EMS with real-time processing)			
Target Value	100%	**Threshold Value**	80%	
Rounding	the criteria for rounding the calculated values (Example : For % calculation, round off to 0% for values between 0.00 and 0.49 and to 1% for values above)			
Unit	%			
Formula	$$\mathrm{KPI}_{04}(\%) = \frac{\sum_{t=1}^{N}\left(P_{m,t} - P_{f,t}\right)^2 - \sum_{t=1}^{N}\left(P_{m,t} - P_{n,t}\right)^2}{\sum_{t=1}^{N}\left(P_{m,t} - P_{f,t}\right)^2} \cdot 100$$			
Calculating frequency	Daily			
Calculation Methodology				
Step	**Description**			
01-	Daily measurements of renewable energy generation			
02	Comparison with related forecasting and error measurement			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Nowcast	mySQL db	10 min	daily	PDM
EMS schedule	mySQL db	10 min	daily	PDM

PLATOON Common Components

KPI N°1				
KPI-Name	IDS Metadata Registry (Boker/Appstore)Integration		**KPI-ID**	1
KPI-Type	Technical			
Description	Metric targeted at the validation of the fact that the IDS Metadata Registry (Broker/Appstore) is able to work together with IDS connectors and Data Analytics Tools Dockers and Marketplace.			
Target Value	1	**Threshold Value**	1	
Rounding	Not applicable			
Unit	Binary 1 or 0			
Formula	If all tools to complete the pilot data analysis are able to interact and send data to each other then this KPI is 1. Otherwise it is 0.			
Calculating frequency	At each pipeline release			
Calculation Methodology				
Step	**Description**			
01-	based on tests the input-output functioning of each pipeline is validated.			
02	Test data is exchanged between the pilot analytics blocks			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Each pilot will have its own dataset connected to IDS connectors.				

KPI N°2			
KPI-Name	DAPS Integration	**KPI-ID**	3
KPI-Type	Technical		
Description	Metric targeted at the validation of the fact that the DAPS provided by Fraunhofer AISEC (not developed in PLATOON) is able to work together with PLATOON IDS connectors, IDS Metadata Registry and IDS Vocabulary Provider.		

Target Value	1		**Threshold Value**	1	
Rounding	Not applicable				
Unit	Binary 1 or 0				
Formula	If all tools to complete the pilot data analysis are able to interact and send data to each other then this KPI is 1. Otherwise it is 0.				
Calculating frequency	At each pipeline release				
Calculation Methodology					
Step	**Description**				
01-	based on tests the input-output functioning of each pipeline is validated.				
02	Test data is exchanged between the pilot analytics blocks				
Data Source					
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner	
Each pilot will have its own dataset connected to IDS connectors.					

KPI N°3			
KPI-Name	Clearing House Integration	**KPI-ID**	4
KPI-Type	Technical		
Description	Metric targeted at the validation of the fact that the Clearing House provided by Fraunhofer (not developed in PLATOON) is able to work together with PLATOON IDS connectors, IDS Metadata registry, DAPS and Marketplace.		
Target Value	1	**Threshold Value**	1
Rounding	Not applicable		
Unit	Binary 1 or 0		
Formula	If all tools to complete the pilot data analysis are able to interact and send data to each other then this KPI is 1. Otherwise it is 0.		
Calculating frequency	At each pipeline release		
Calculation Methodology			

Step	Description			
01-	based on tests the input-output functioning of each pipeline is validated.			
02	Test data is exchanged between the pilot analytics blocks			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Each pilot will have its own dataset connected to IDS connectors.				

KPI N°4			
KPI-Name	PLATOON Marketplace GUI Integration	**KPI-ID**	5
KPI-Type	Technical		
Description	Metric targeted at the validation of the PLATOON Marketplace is able to work together with PLATOON IDS Metadata Registry, DAPs and Clearning House.		
Target Value	1	**Threshold Value**	1
Rounding	Not applicable		
Unit	Binary 1 or 0		
Formula	If all tools to complete the pilot data analysis are able to interact and send data to each other then this KPI is 1. Otherwise it is 0.		
Calculating frequency	At each pipeline release		
Calculation Methodology			

Step	Description			
01-	based on tests the input-output functioning of each pipeline is validated.			
02	Test data is exchanged between the pilot analytics blocks			
Data Source				
Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Each pilot will have its own				

dataset connected to IDS connectors.				

KPI N°5			
KPI-Name	IDS Vocabulary Provider Integration	**KPI-ID**	2
KPI-Type	Technical		
Description	Metric targeted at the validation of the fact that the IDS Vocabulary Provider is able to work together with PLATOON datamodels repository, IDS connectors and DAPs.		
Target Value	1	**Threshold Value**	1
Rounding	Not applicable		
Unit	Binary 1 or 0		
Formula	If all tools to complete the pilot data analysis are able to interact and send data to each other then this KPI is 1. Otherwise it is 0.		
Calculating frequency	At each pipeline release		
Calculation Methodology			
Step	**Description**		
01-	based on tests the input-output functioning of each pipeline is validated.		
02	Test data is exchanged between the pilot analytics blocks		
Data Source			

Data description	**Data source**	Data collection frequency	Data collection time range	Data Owner
Each pilot will have its own dataset connected to IDS connectors.				

References

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