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Terms and abbreviations

CO	Confidential
EC	European Commission
IMP	Individual Mentoring Plan
MVP	Minimum Viable Product
PU	Public
TTP	Technology Transfer Programme
WP	Work package
PoC	Proof of Concept

Executive Summary

This document summarises the Technology Transfer Programme for the PLATOON Open Calls performed as part of WP7. The report includes an explanation of the support programme and a summary of all the 13 open call projects including objectives, results and deviations. All the details about each specific project can be found as part of Open Call Milestone Deliverables available on https://gear.fundingbox.com/.

1 Introduction

This document summarises the Technology Transfer Programme for the PLATOON Open Calls performed as part of WP7. The report is organized in 3 main sections:

1. Section 2 includes an explanation of the Technology Support Programme.
2. Section 3 summarises all the 13 open call projects including objectives, results and deviations.
3. Finally, section contains the main conclusions drawn as part of the TTP.

All the details about each specific project can be found as part of Open Call Milestone Deliverables available on https://gear.fundingbox.com/ .

2 Technology Support Programme

The aim of the Technology Transfer Programme was to support the open call beneficiaries with the execution of the bottom-up projects. The programme lasted 9 months and consisted of 2 stages:

- **Stage 1 - Inception.** The first step of the programme was to engage the talent and build up the best mentoring set-up. Selected teams met during a Welcome Event where they were matched with a technical mentor. After that, the teams worked intensively over a 4-week period to define their Individual Mentoring Plan (IMP). This document established the KPIs and Deliverables that were taken into account when the Mentoring Committee evaluated the bottom-up projects' performance during the review process (see section 2.1). As a result of this stage, a Proof of Concept (PoC) is defined together with the mentors, including the roadmap to successfully execute the project (by the end of M2 of the programme).

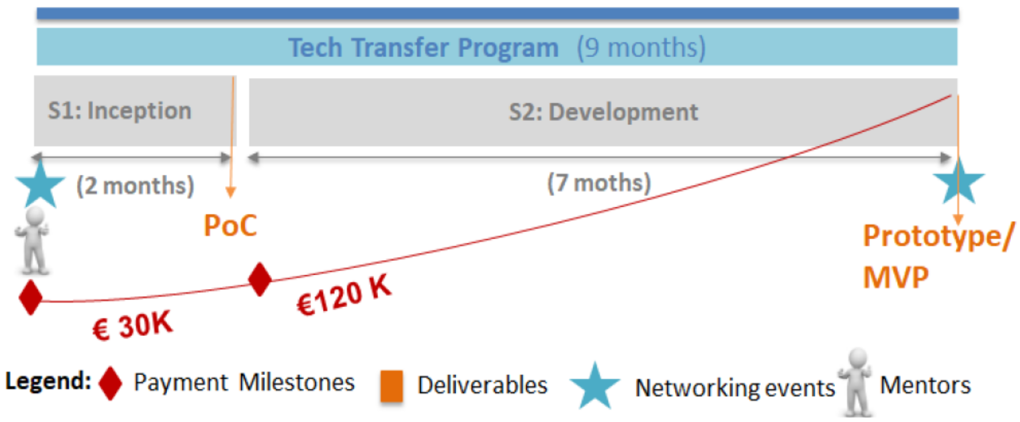


Figure 1 Stages of the Technology Transfer Programme

- **Stage 2 - Development.** This stage focused on developing a prototype/MVP based on the PoC defined in the previous stage. The outcome of the programme was either a Prototype (1st Open Call) or an MVP (2nd Open Call).

2.1 Review process

The validation of milestones was carried out in three steps, and the fourth step was payment release. Figure below represents the steps that were taken from milestones' evaluation until the payment release.

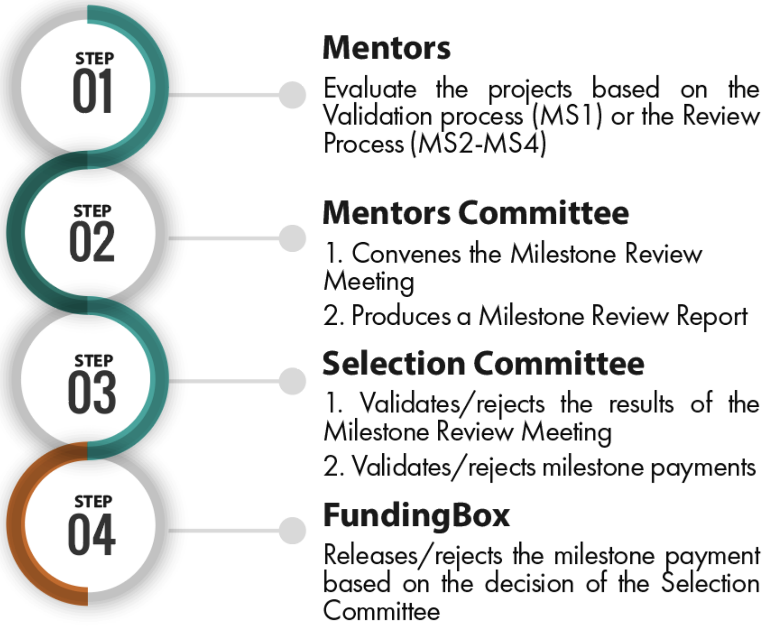


Figure 2: Validation and payment steps

Milestones' evaluation (step 01 on the figure above) was implemented consisting of the following evaluation criteria (see also figure below):

- Deliverables' quality.
- Technical performance indicators.
- Deadline Compliance.

Each criterion was scored by Technical Mentors from 0 to 10 and the weight of each one of these criteria, in the final score, was as follows:

- Deliverable quality (45%).
- Technical performance indicators (45%).
- Deadline Compliance (10%).

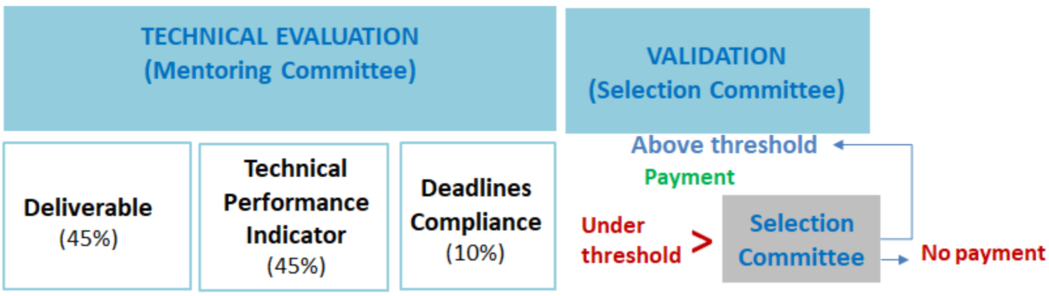


Figure 3 Weight of each evaluation criteria

2.2 Technical Mentor Assignment

The Technology Transfer Programme explained above was led by mentors who were selected specifically for each of the projects. The list of mentors was composed based on their competence and participation in pilots. The table below shows the list of mentors for the first and second open calls:

Table 4: PLATOON 2nd Open Call - Technical Mentors

Project Number	Company name	Project Title	Pilot	Mentor
01	Advanced Infrastructure	High Resolution Photovoltaic Forecasting Toolbox	2A	Valentina Janev (IMP)
02	Nissatech	High precise cognition-driven maintenance service for energy systems	2B/1A	Jose Barriga (IND)
03	Builtrix	Predictive Renewable Energy source and Demand optimization Tool for buildings	3B (Roma Capitale) / 3B(Poste Italiane)	Patrick Maurelli (ROM)
04	MIPU Energy Data s.l.r	SOLar forecaST In dynamiC Environments	4A	Marco Mussetta (PDM)
05	Atlantis Engineering SA	Predictive Maintenance for Performance Optimization of Energy Assets	3B (Poste Italiane)	Martino Maggio (ENG)
06	Barbara IoT	Federated Edge Platform	3A/3C	Philippe Calvez (ENGIE)/ Erik Maqueda (TECN)

Table 5: PLATOON 2nd Open Call - Technical Mentors

Project Number	Company name	Project Title	Pilot	Mentor
07	PLEGMA LABS TECHNOLOGIKES LYSEIS ANONYMOS ETAIRIA	Energy oPtimization of building IOT Infrastructures in a Stratified way	2A	Valentina Janev (IMP)
08	Rebasian Technologies AB	Enerflow	2A	Erik Maqueda (TECN)
09	RENN Solutions d.o.o.	AURORA	4A	Marco Musetta (PDM)

10	Heliocity	Heliocity	3C	Ivan Sanchez/Luis Garcia (GIR)
11	Apio S.R.L.	Venera	3B ROM	Patrick Maurelli (ROM)
12	DG Twin S.r.l.	INvolving hydrogen for a GReener and Innovative energy Deployment	4A	Philippe Calvez (ENGIE) / Marco Musetta (PDM)
13	AITL Limited	High Resolution Demand Profiles for Tranfomer Digital Twinning	2B	Pau J. Cortes/Adrià Serra (SAM)

Finally, Tecnalia coordinated the different mentors for each of the Open Calls as part of the Technical Mentoring Committee.

3 Open Call Projects

This section summarises all the 13 open call projects including objectives, results and deviations.

3.1 High Resolution Photovoltaic Forecasting Toolbox

3.1.1 Objectives

The objectives of the present project were the following:

1. FEASIBILITY STUDY: Produce a documented report on the feasibility of the containerisation of PV_Live analytics system as a deployable software product and to confirm that the requirements will be met.

2. TO DOCUMENT THE DATA AVAILABILITY REQUIREMENTS: Produce a data architecture and data requirements document for the PV Monitoring and the PV Forecasting datasets. Identify whether the required data quality from the pilot region to successfully create a prototype PV Monitoring and Forecasting analytics system is available and utilise to create a Proof of Concept for Pilot Country.

3. TO BUILD INFRASTRUCTURE Proof of Concept: Build a functional Proof of Concept of the containerised version of the PV Monitoring and Forecasting analytics software and data systems on a new infrastructure platform.

4. TO BUILD PROTOTYPE USING SUITABLE DATA FROM PILOT: Utilise Pilot Country Data to create prototype Monitoring and Forecast Outputs from the analytics system on a new infrastructure platform compatible with PLATOON Reference Architecture.

3.1.2 Results

Implemented cloud containerised PV monitoring service in IMP premises and compared with the existing commercial implementation as used by the UK system operator, with a second implementation in UK based on PV output data.

The figure below shows the validation statistics for GCP implemented GB out turn monitoring compared with on-premises operational solution. GCP plus PV output data over estimates out turn by 4 % in comparison with on-prem plus Passiv systems data.

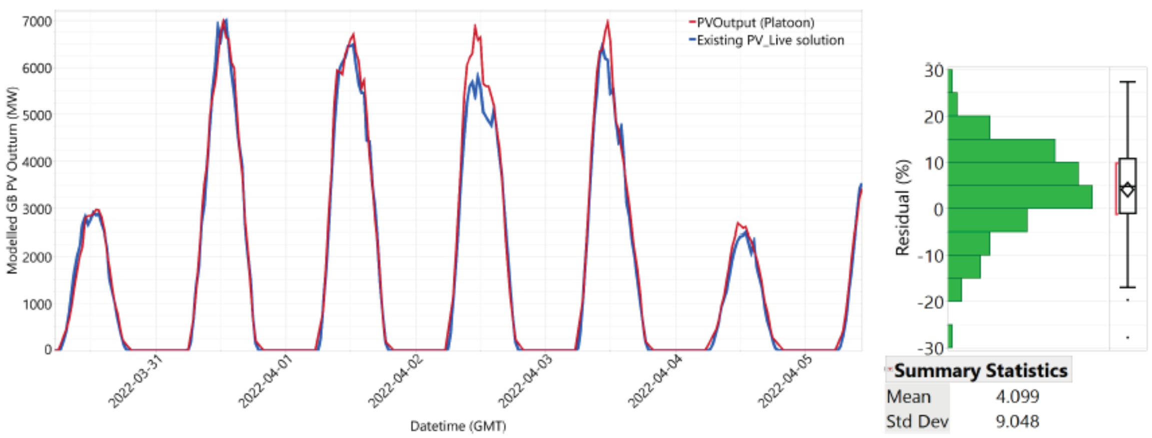


Figure 4:Validation statistics for GCP implemented

Table 6: Data quality comparison between current operational service and the Platoon implementation

	Current operational service On-prem using bespoke platform and data service	**Platoon implementation** GCP-hosted using open data from PVOutput.org
Number of sample systems	~1000 intraday ~20k on day+1	~575
Quality of metadata 1. Location accuracy 2. Capacity (AC or DC) 3. Orientation 4. Multi-array	1. Full postcode (~ 100m in urban areas) 2. DC 3. Mostly 4. No	1. Outward postcode (~ 1 km in urban areas) 2. DC with less confidence 3. Sometimes but less reliable 4. No
Out-turn comparison Difference between GCP/PVoutput.org out-turn and existing operational service on first deployment	4% bias - PVOutput solution over-predicts 9% standard deviation Target is < 5% error.	

Monitoring and forecasting has been implemented for the extended Balkan region using real time data from systems in Hungary, Romania, Bulgaria, Slovakia, Slovenia, Serbia et. The location of sample systems is shown in shown in the figure below.

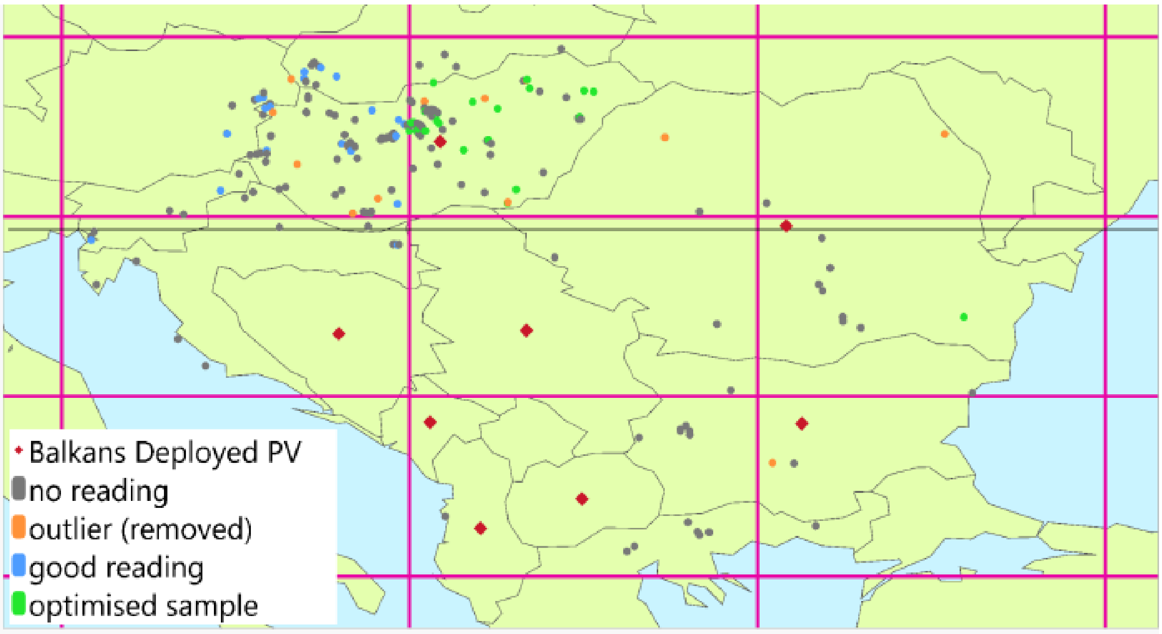


Figure 5: Extended Balkan region implementation - Location of available sample systems

The figure below shows an example of the aggregated output from the Balkan region In March 2022 with a peak around 2.3 GW.

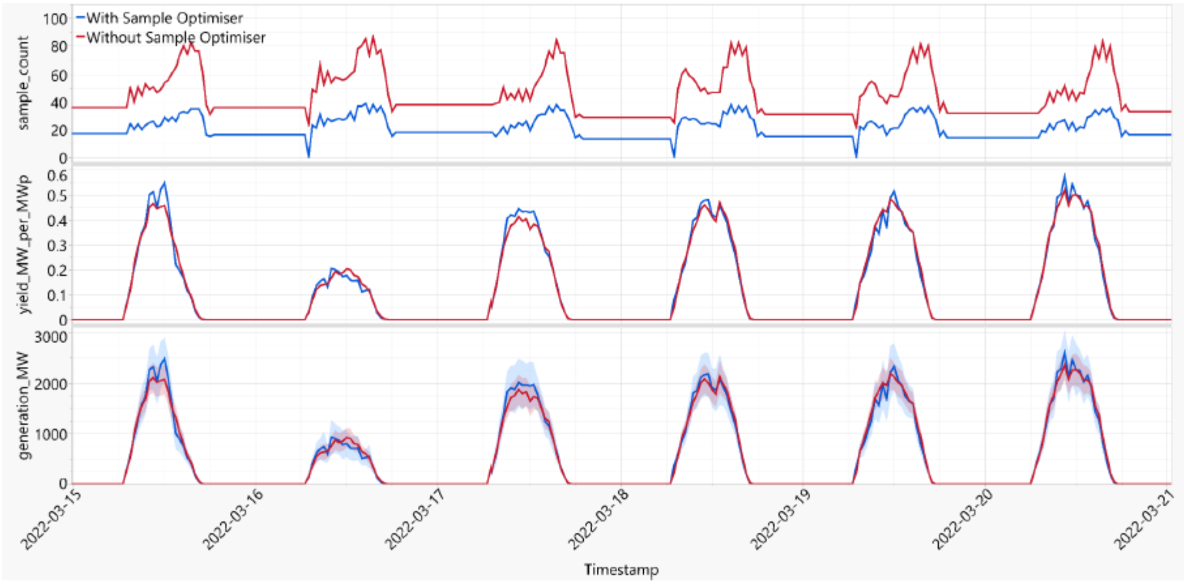


Figure 6: An example of the aggregated output from the Balkan region is shown below. In March 2022 output peaked at

3.1.3 Conclusions

Platoon implementation returns monitoring data 4% higher than the commercial GB solution with a statistical error of around 10%. The variation largely comes from differences in the quality of the source data.

3.2 High precise cognition-driven maintenance service for energy systems

3.2.1 Objectives

The objectives of the present project were the following:

1. Develop new system for cognition-driven predictive maintenance (Cogni4Main, TRL6), which will enable proactive detection of the problems, indicating the need for maintenance activities.

2. To develop a predictive maintenance tool for LV/MV transformers, based on the system from Objective 1. This tool will use available data in this kind of installations or installing new sensors considering the small budget normally used in LV/MV transformers.

3. Successful deployment in the selected pilot (UC-2B-01), resulting in the fulfilment of defined KPIs.

4. Validation of the developed system(based on Objective 3).
5. Wider promotion of the system in the energy domain.

6. Planning commercialization of the developed system.

3.2.2 Results

A cognition-driven predictive maintenance tool (Cog4Main) for LV/MV transformers was developed and implemented in pilot 2B:

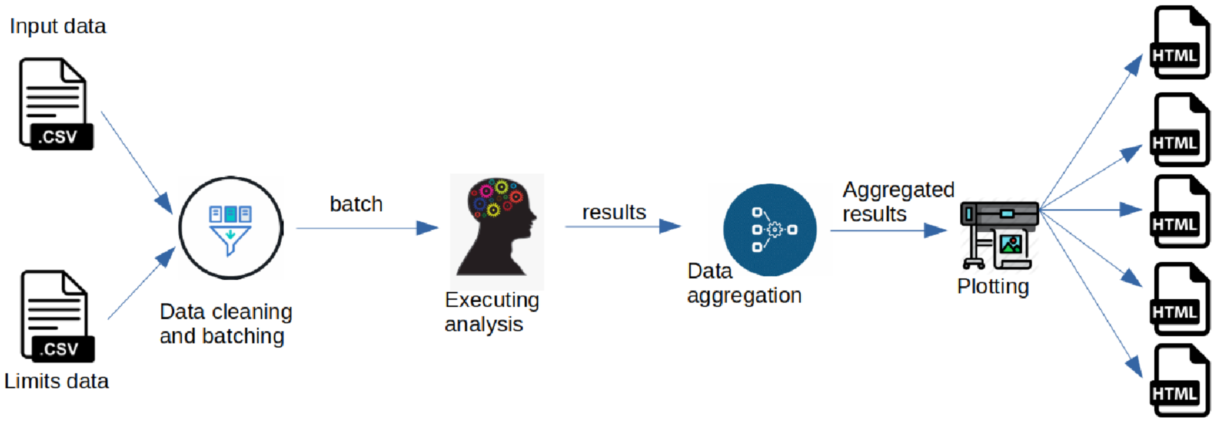


Figure 7 : System Architecture

The implemented system was validated using available data in Sampol´s smart grid in ParcBit, Majorca (Spain) in Pilot 2B. The figure below shows an example of the validation results:

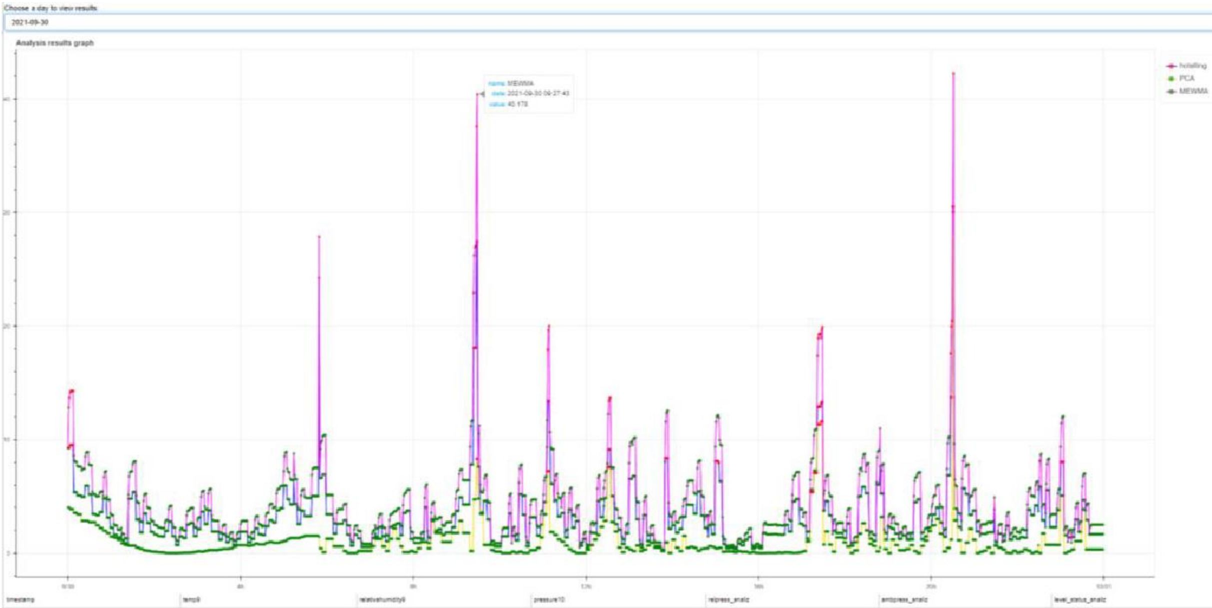


Figure 8: Cognition-driven predictive maintenance tool – validation results

Figure 9: Cognition-driven predictive maintenance tool - validation results temperature monitoring

Some outliers were detected and its root cause was analysed:

Table 7: Example Detected outliers

Timestamp	Outlier	Variations	Unusuality	Comment
2021-08-12 18:15:00	True	True	True	Sensor communication problem
2021-11-22 00:11:00	True	True	True	Sensor communication problem

3.2.3 Conclusions

The developed tool was successfully implemented and validated in pilot 2B. The analysis of the validation results has shown that:

- All anomalies which our system has found with a high probability are true positives!
- Anomalies which our system has found with a lower probability are partially false positive

Therefore, the approach has been positively evaluated for the anomalies which are detected with high confidence. For the rest, the system is still unprecise (discovering false positive anomalies) and will be further improved beyond the project.

3.3 Predictive Renewable Energy source and Demand optimization Tool for buildings

3.3.1 Objectives

The objectives of the present project were the following:

1. Build a solution that can automatically analyze the big data coming from electricity smart meters. This could be achieved through spatial reporting services that include GIS visualization for the Buildings Energy Consumptions (EC) and general energy performances (EP).

2. Build a solution that can benchmark the energy consumption & performance in buildings.

3. Build a solution that can predict the energy consumption in buildings.

4. Build a solution that can help Roma Capitale to understand the PV potential of their buildings, also in relation to the opportunities coming from Energy Community model and incentives.

3.3.2 Results

A spatial reporting tool was developed. In this service end-users can explore building's, electricity, and gas smart meter's metadata based on their location in the Rome GIS visualization. Buildings are categorized by their type (specific usage type) to enable end-users for concentrating on specific type of assets. Users can also filter address, POD, and PDR codes, as well as Site and Building ID.
The GIS map database is connected to the consumption database, and so, the end-user can visualize the gas and electricity consumption (historical and forecasts). Thanks to the access to higher resolution electricity consumption data, the daily consumptions are available for the user by clicking on the monthly graph. Thus, end-user can select 1 or more months to visualize daily trends in the hit map.

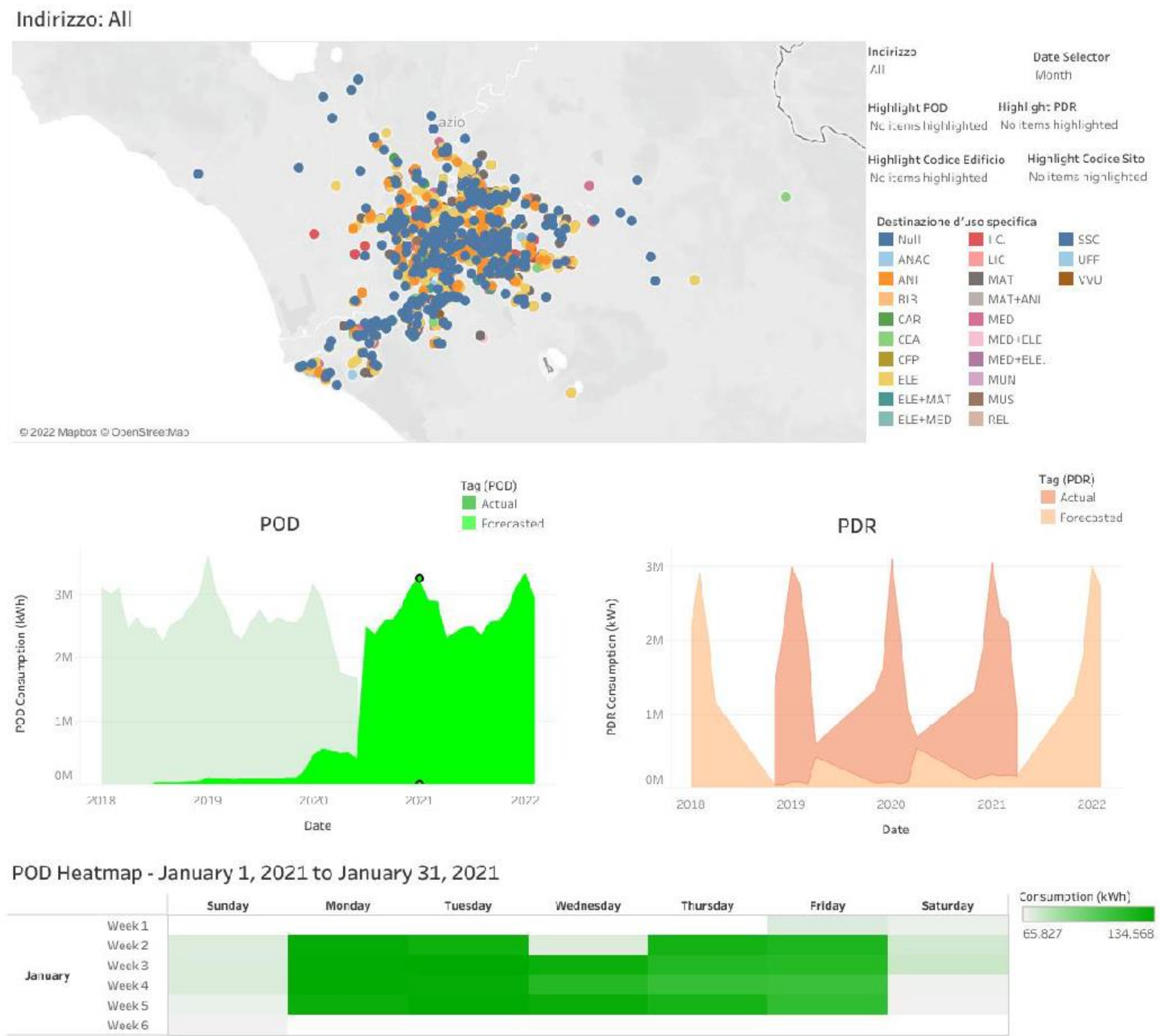


Figure 10: Spatial Reporting tool

In addition, a Benchmarking tool was developed. The benchmarking service has 5 main elements including two tables and three graphs. The left section of tables presents the statistical indicators of buildings in annual basis. The right sides (Mean) are connected to the clusters and create a benchmark reference for each indicator. Therefore, selecting building type will change the right side of tables with average values in the cluster. This is also mixed with graph visualization. The end-user sees buildings based of their area and consumption level, then benchmark them based on the performance (kWh/m2). This visualization can be tracked over years, including the forecasting data. This service helps end-user to understand which assets are in priority for energy efficiency action plans. End-users can filter addresses or keep them from spatial reporting service.

The last graph is the clustering graph on GIS map which shows the buildings in different clusters according to their area, construction type, and usage type. We have added a rule based natural language processing algorithm to this graph to explain the clusters as the caption of the widget.

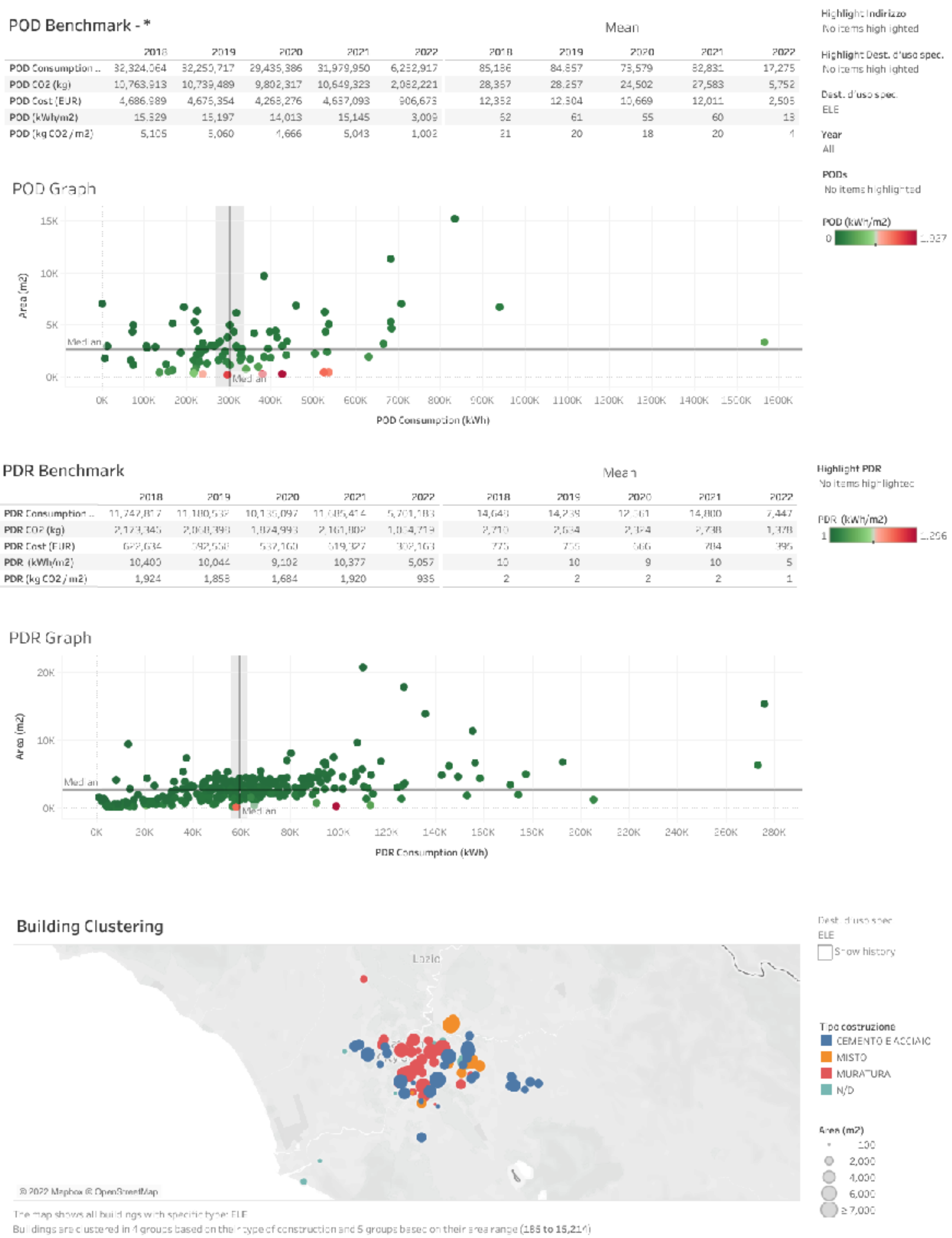


Figure 11: Benchmarking tool

Furthermore, a Forecasting tool was developed. In this service the electricity and gas consumptions are forecasted for the next 24 months. End-users are able to evaluate days of week and weeks of months and set priority for saving action plans.

Besides, the historical PDR (gas) data is only available for the cold months and this data model is kept through the forecasted data. It is noticeable that there are “forecasted” tags on the consumption data of before March 2020 which is the last date in the shared batch data. This is because there were missing data for several buildings in various hours and in some cases for several days. So, the forecasting model is used for re-generation of missing data.

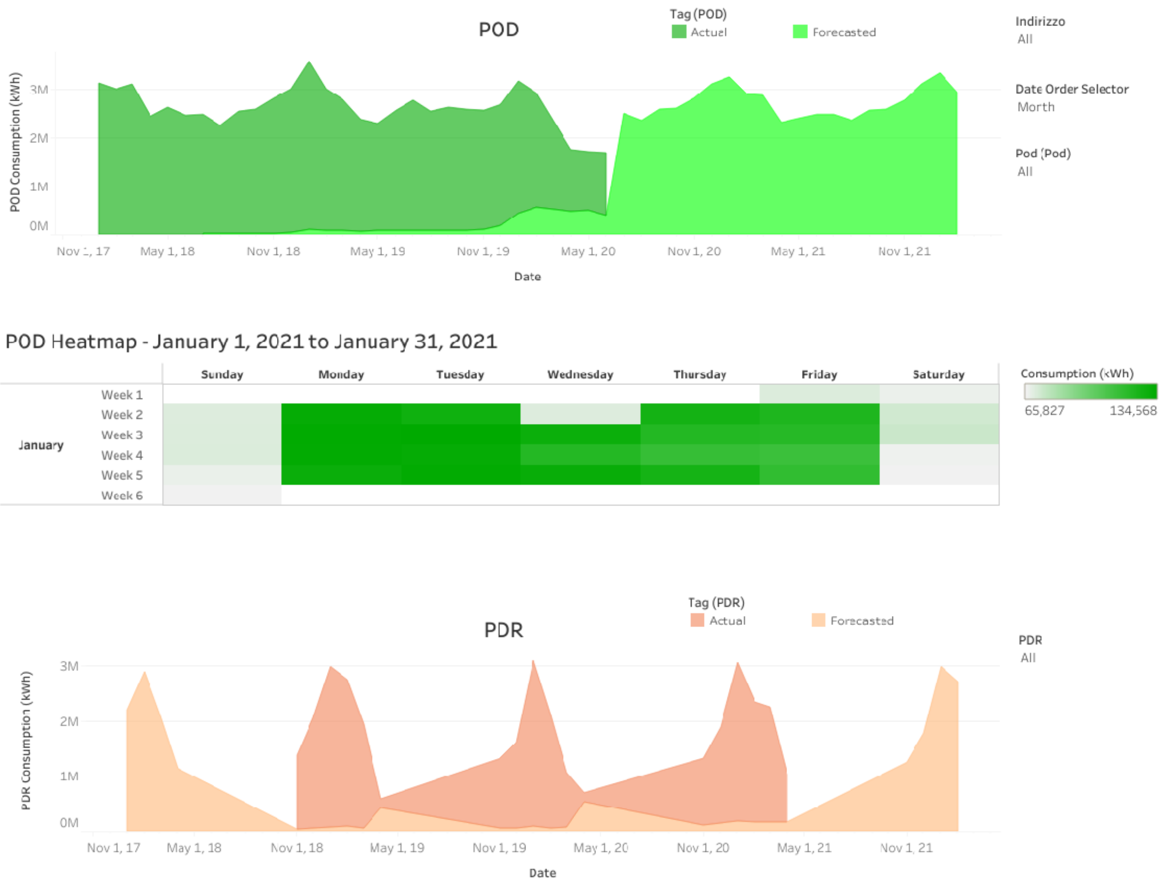


Figure 12: Forecasting tool

Finally, a RES potentialities tool was developed. This service was the core of PREDICT project and has 7 widgets. The one on the top shows the building rooftop geometry including existing plant, unused area, and void spaces. The information about the number of panels, their capacity in Wp, their slope, and azimuth angle are visible in this widget.
The estimated PV generation widget is added bellow the GIS visualization. The end-user can see the production data with resolution up to hourly data which is then used for the estimation of existing plant efficiency in comparison with the data from Lovato portal.
The consumption and generation datasets (and their short-term forecasts) are combined to create the monthly and annual analysis tables. These tables are dependent of energy market indicators such as utility and trade tariffs as well as the size and type of PV plants.
The self-consumption analysis widget shows the possibility and area of plants needed for 100% building energy decarbonization. The return on investment (ROI) analysis widget shows the project capital cost based on the PV panel market data. Also, it includes the estimated capital cost of deploying such project. The rule-based NLP service is used for describing the widgets and creating a complete PV investment report for the end-users.

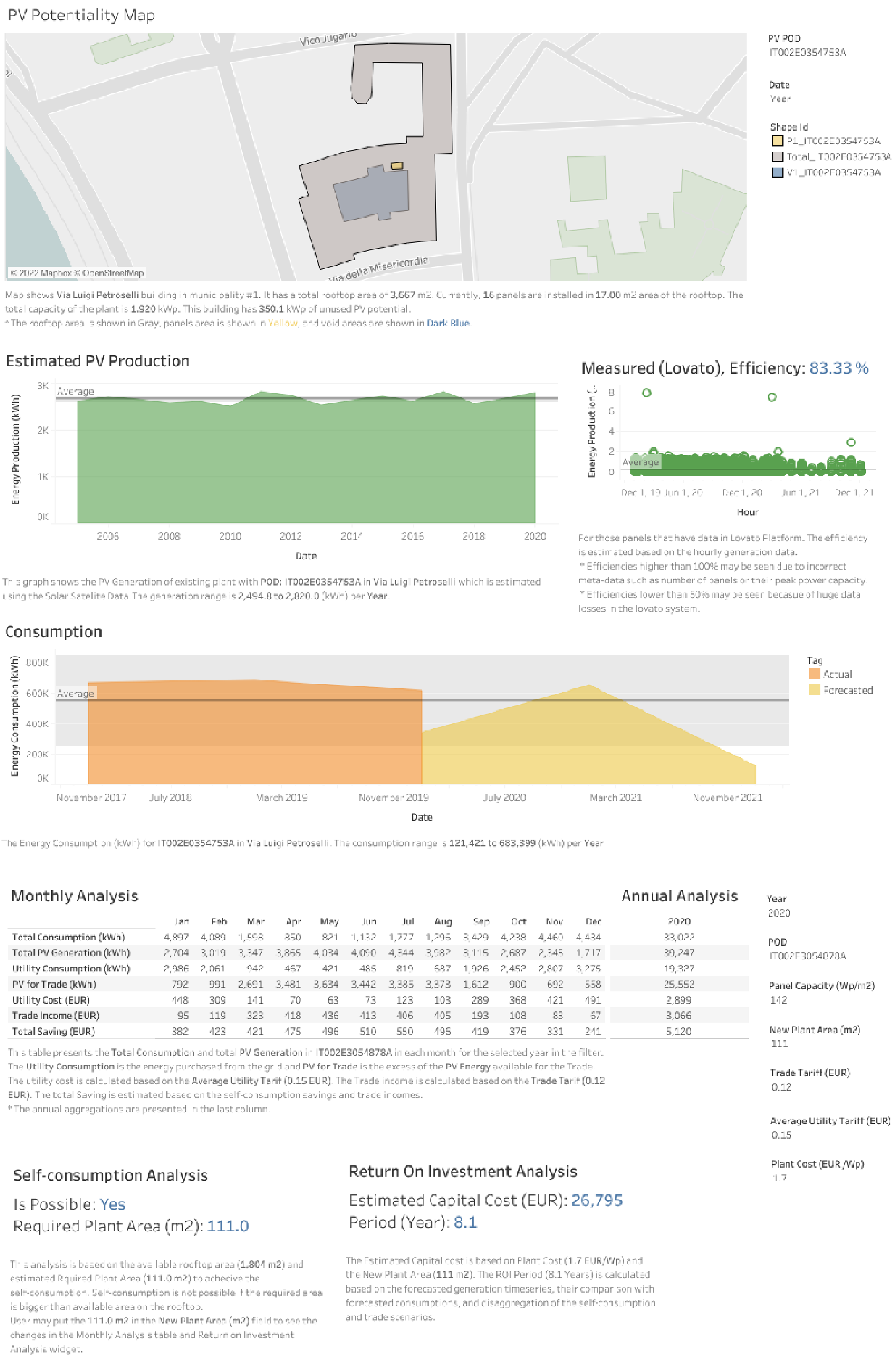


Figure 13: RES potentialities tool

All the tools were integrated with the Digital Enabler Platform provided by ENG which is part of PLATOON federated platform.

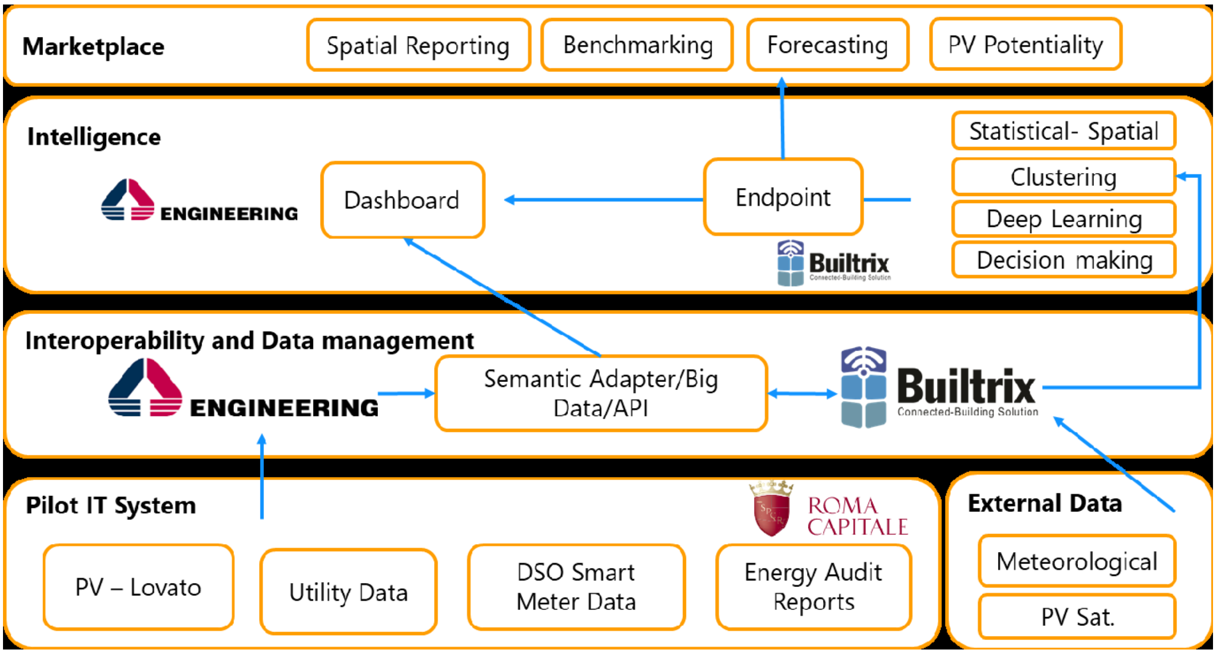


Figure 14: ICT architecture

3.3.3 Conclusions

All the tools were successfully developed and integrated with ENG Digital Enabler Platform. A Geolocation widget was developed and validated including geolocation information of all 1237 buildings from ROM. An energy consumption benchmarking and forecasting algorithm were developed and validated showing an accuracy over 80%. An algorithm for the evaluation of the PV potentiality of rooftops in 145 ROM buildings. The method was developed with static entries from end-users in terms of utility and trade tariffs. In future, if a dataset regarding a community around each ROM building is available (characteristic, regulation, consumption, prediction, potential), it would be possible to relate the trading of energy with self-consumption of each building and introduce it to the optimizer as an additional constraint.

3.4 SOLar forecaST In dynamiC Environments

3.4.1 Objectives

The objectives of the present project were the following:

1. Design, develop, train and test a machine learning based computational algorithm that predicts the PV production with a 24h horizon, based on weather forecasts and PV modules operating conditions.

2. Ensure timely fruition of forecasting results on Platoon platform.

3. Provide different levels of geographic and temporal aggregation for forecasting results.

4. Provide estimation of the uncertainty surrounding the prediction(forex. confidence intervals).

5. Provide meaningful visualisations of predictions.

6. Monitor predictive model performance to identify the best re-training schedule.

7. Ensure seamless integration between IDS connectors, Platoon platform and SOLSTICE data analytics toolbox.

8. Based on a feasibility assessment, implementation of experimental features of forecasting algorithms in the Data Analytics Toolbox. Provision of Dynamic predictions based on weather forecasts updates and asset health status.

9. Based on a feasibility assessment, implementation of experimental features of the machine learning pipeline: provision of auto-machine learning features in the Data Analytics Toolbox for automated, code-free modelling of newly ingested data.

3.4.2 Results

The SOLSTICE analytics tool has been deployed according to the on-premises installation framework.
Apart from the sensors already installed in pilot 4A, latitude, longitude, altitude and turbidity were retrieved. The algorithms were validated with real data from pilot 4A.
The XGB model, trained on PV3 was applied to predict produced power of PV1 and PV2.

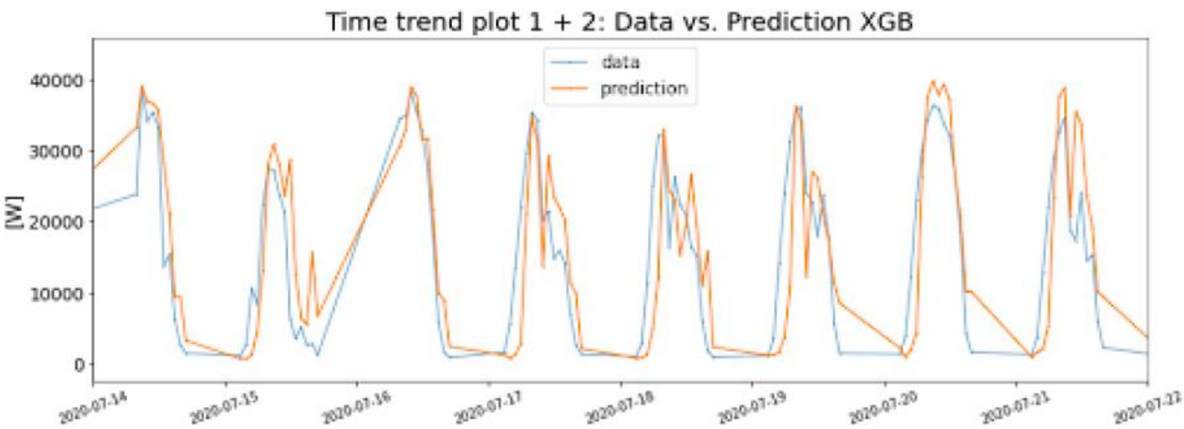


Figure 16: Validation Results of the model

3.4.3 Conclusions

The solar forecasting algorithm was successfully developed and validated showing a normalized error (nMAE) of around 11.37%. Also, it is interesting to note the ability of the model to transfer its prediction capabilities also on PV modules whose information were not included in the training phase of the algorithm.

3.5 Predictive Maintenance for Performance Optimization of Energy Assets

3.5.1 Objectives

The objectives of the present project were the following:

1. Process the stored data to identify any significant statistical correlations and compute statistics regarding the distribution of the data, which Will be useful for the anomaly detection analysis.

2. Adapt the implementation of the anomaly detection algorithms to the Poste Italiane use case. Configure or train appropriately the algorithms and process the data to identify abnormal behaviour in the heating and cooling system to generate alarms.

3. Integrate the anomaly detection services to the Platoon platform and obtain current data from Poste Italiane for processing.

3.5.2 Results

PreMATE fault detection solution was implemented and validated. Three detection approaches have been implemented and applied to the data.

1. Fault Detection based on Bounds, which is a simple rule-based non-supervised approach that is called Rule-Based Detection
2. Fault Detection based on Spikes, which is supported by a state-of-the-art Outlier Detection Algorithm for Streaming Data, called Micro-cluster Continuous Outlier Detection (MCOD) (Kontaki, Gounaris, Papadopoulos, Tsichlas, & Manolopoulos, 2011). It's a non-supervised Detection method.
3. Fault Detection based on Trends, which uses a Linear Regression approach to estimate the future trend of the measurements and requires a portion of the testing data set to be dismissed and utilized in the training process.

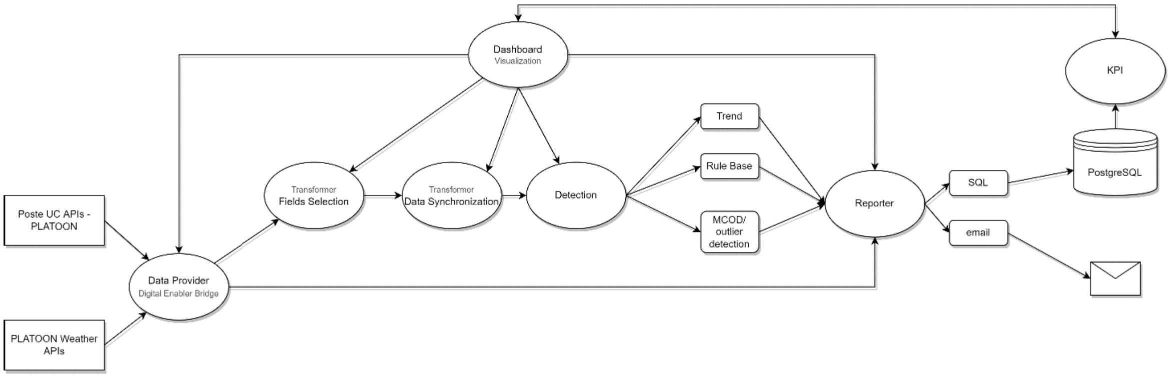


Figure 17: PREMATE - ICT Architecture

The results of the 3 detection methods were successfully validated and integrated into a Grafana visual dashboard as shown in the figure below:

Figure 18: Validation Results

Finally, an intra- and inter-component integration tests were performed in order to reassure the proper communication between all the components of PreMATE and the external systems. The intra-component integration refers to the communcation between the components for PreMATE, while the inter-component integration refers to the communication of PreMATE with the DigitalEnabler tools.

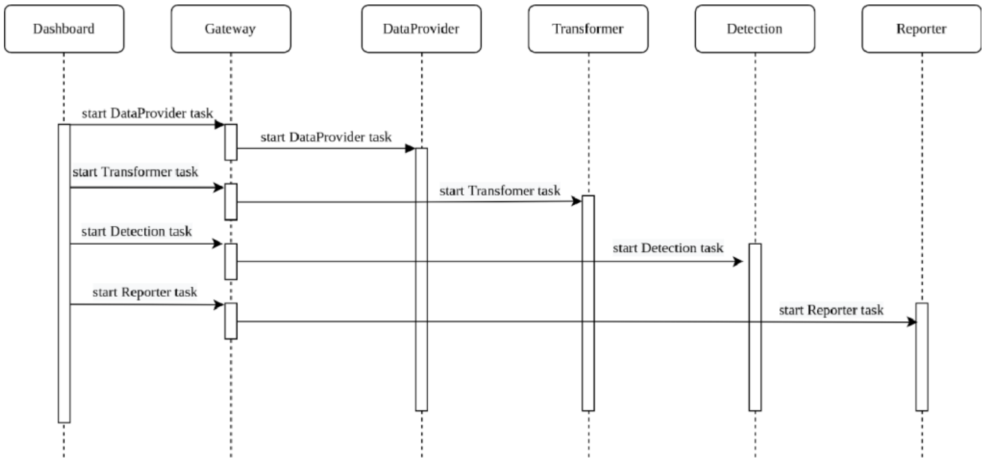


Figure 19: Example of inter-component integration test

3.5.3 Conclusions

Interesting outcomes were produced from the correlation analysis checking for linear, non-linear correlation and seasonality. Delta-temperature with relative energy consumption is significantly correlated (i.e., 70% correlation). In addition, several hypotheses had been put to test like the effect of the idle periods (e.g., on Sunday building are closed) to the energy consumption of the next working day (i.e. increased consumption).
All the intra- and inter-component integration test along with the functional test were successfully passed.

3.6 Federated Edge Platform

3.6.1 Objectives

The objectives of the present project were the following:

1. Modify or extend existing IDS connector(s) to work in a Barbara OS powered Edge Computing Node with real time (i.e. not batch) sovereign data exchange and computing capabilities.

2. Modify or extend existing Context Broker(s) to work in a Barbara OS powered Edge Computing Node.

3. Integrate IAM data provenance services(i.e. DAPS and Clearing House) used in PLATOON and provided by Fraunhofer AISEC into a Barbara OS powered Edge Computing Node.

4. Be able to control de lifecycle of the software (deploy, configure, and update) using an Edge-Cloud framework, extended by Barbara Panel.

5. Execute the building occupancy algorithm at the Edge with camera data and sent the results externally via the Connector and the Context Broker in pilot 3A.

6. Execute the predictive maintenance algorithm at the Edge with sensor data and sent the results externally via the IDS Connector and the Context Broker in pilot 3C.

3.6.2 Results

A Federated Edge Platform was developed based on Barbara Panel and aligning with the PLATOON reference architecture, specially, around IDS part. In
Most of the services were provided through the Barbara Operating System, which is a security-oriented Operating System that runs in IoT Edge Devices and Gateways. Barbara Panel is a cloud service which is used to remotely manage Barbara OS powered devices.

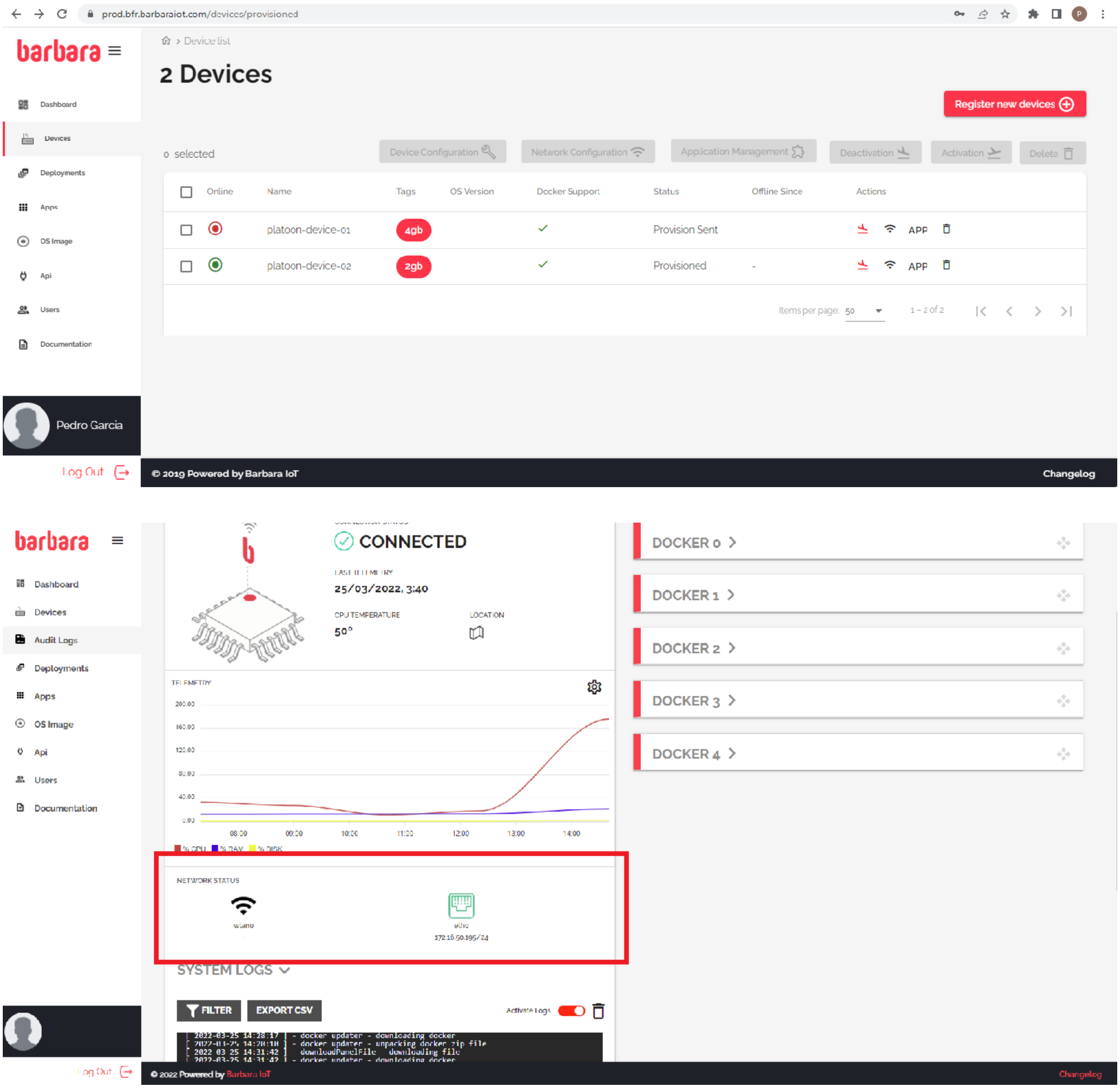


Figure 20: Barbara Panel

In PLATOON project an IDS connector at the edge was developed and implemented based on the TRUE connector developed in PLATOON project. In addition, different data analytics tools developed in WP4 were implemented in the developed Federated Edge Platform and validated using real large scale pilot data from pilots 3A and 3C.

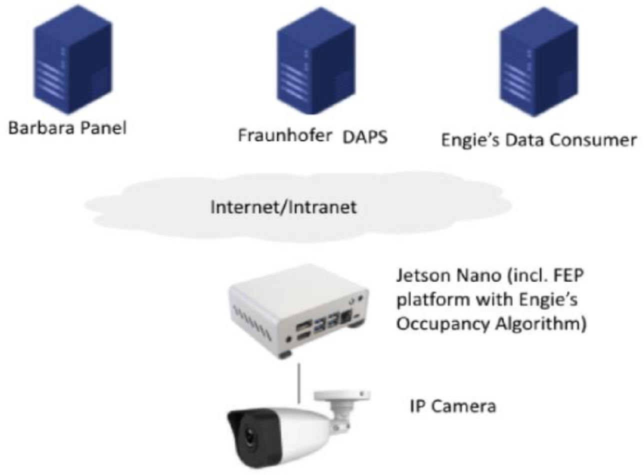


Figure 21: Pilot 3A - ICT Architecture

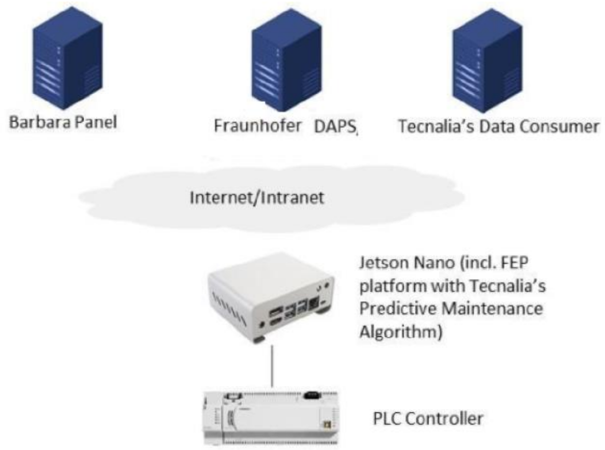


Figure 22: Pilot 3C - ICT Architecture

A detailed validation plan was successfully completed for both use cases. Figures below show the validation results for each of the use cases:

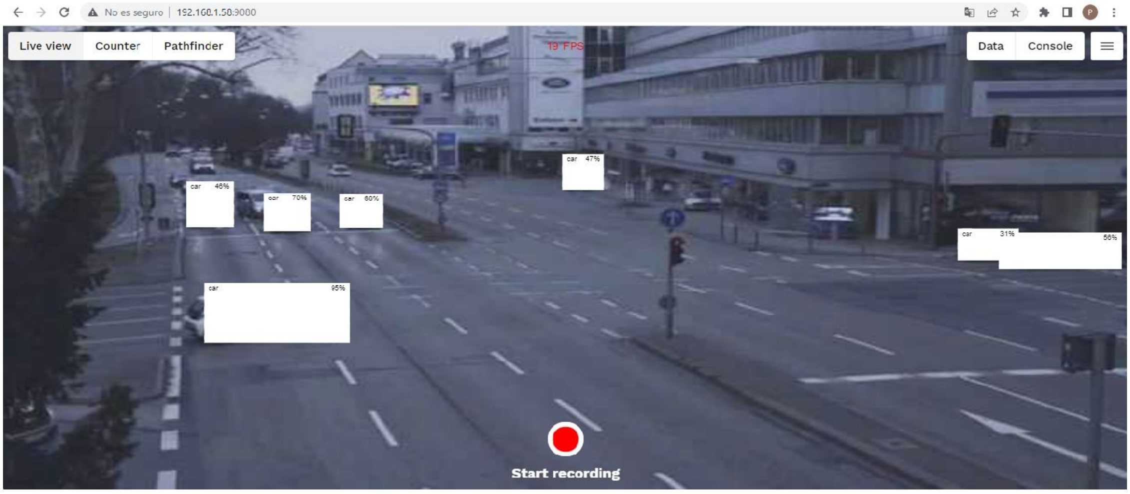


Figure 23: Pilot 3A - Validation Results

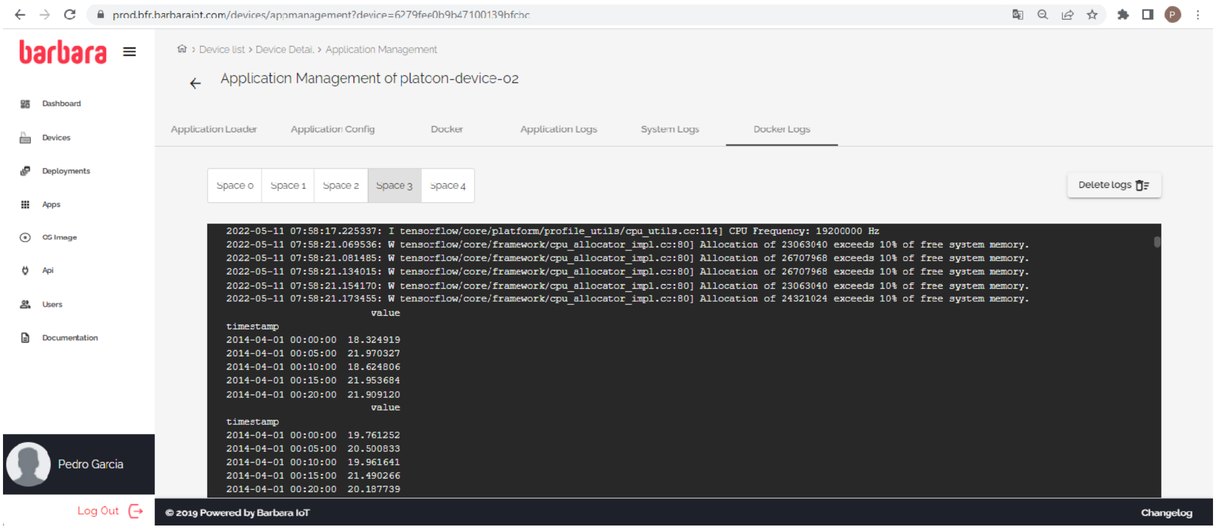


Figure 24: Pilot 3C: Validation logs

3.6.3 Conclusions

A federated edge platform was successfully implemented and validated in pilots 3A and 3C. The end-to-end validation was completed. The only component that could be tested was the Clearing House due to issues with the server from IAIS at the time. As part of the project an open-source IDS connector based on TRUE connector was developed and implemented. The developed components was made public in the PLATOON GitHub repository https://github.com/PLATOONProject.

3.7 Energy oPtimization of building IOT Infrastructures in a Stratified way

3.7.1 Objectives

The objectives of the present project were the following:

1. Produce a documented report on the reproducibility of the e-PIOTIS deployable software product and confirm that the requirements will be met.
2. Produce a data architecture and data requirements document for the e-PIOTIS working prototype. Identify which data inputs are required to create the Proof of Concept.

3. Build a functional Proof of Concept of the e-PIOTIS AI-enabled Energy Management System (EMS) and deploy it in the PLATOON ecosystem.
4. Utilise validation data to create a prototype compatible with the PLATOON Reference Architecture.

3.7.2 Results

For the purposes of the e-PIOTIS project demonstration, real data were continuously collected from one of PLATOON's pilot sites (PLATOON pilot #2A), where the modules where deployed. Namely, Institute Mihajlo Pupin, which is based in Belgrade, Serbia, provided historical and real-time data for one building located in its facilities.

A neural network model was developed with TensorFlow as a Hierarchical Data Format (.h5) file and the microservice API was developed using Python, Flask, and Docker. API endpoints were utilized to make hourly forecasts for the next 48 hours with the trained model with a cron job scheduled to run every night, using weather forecasts for the respective area (Belgrade, Serbia for the PLATOON pilot use case). The end-user, Institute Mihajlo Pupin in this case, was then able to fetch 48-hour ahead forecasts using the "/api/getForecast/Pupin" endpoint from the deployed docker container service.
In the figure below the PV production predictions are compared against the actual measured values for 300 hourly time slots regarding the data from Institute Mihajlo Pupin.

Figure 25: PV production prediction

In addition, a machine learning model training pipeline for the building energy demand forecasting module was developed based on the available data. Open datasets and Plegma Labs' proprietary data from 4 different commercial buildings were utilized to conduct experiments to choose the appropriate neural network model architecture based on the achieved prediction errors. The respective prediction evaluation plots are presented in the following figures:

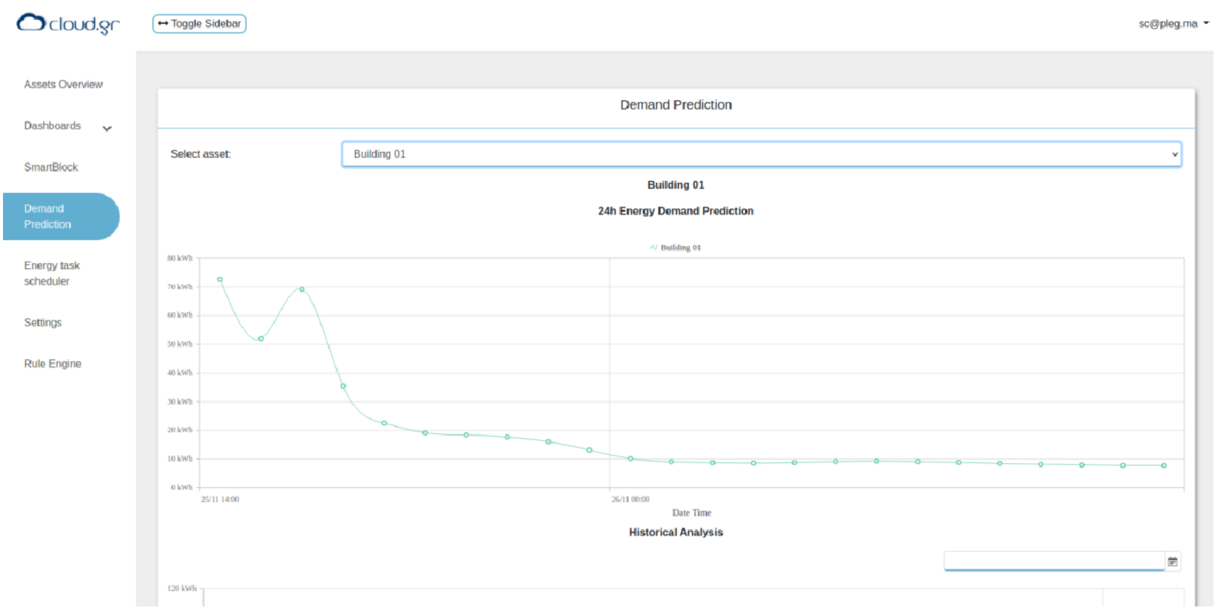


Figure 26: Demand Prediction

In addition, a machine learning model training pipeline for the HVAC energy demand forecasting module was developed based on the available data. Open datasets and Plegma Labs' proprietary data from one HVAC installation were utilized to conduct experiments to choose the appropriate neural network model architecture based on the achieved prediction errors. Regarding the HVAC energy demand forecasting module, the top-performing model was a GRU RNN that achieved a WMAPE of 17%. The neural network pipeline deployment was conducted through the same infrastructure with the demand forecasting module, as described in the previous subsection. The HVAC forecasting evaluation plot is presented in the following figure:

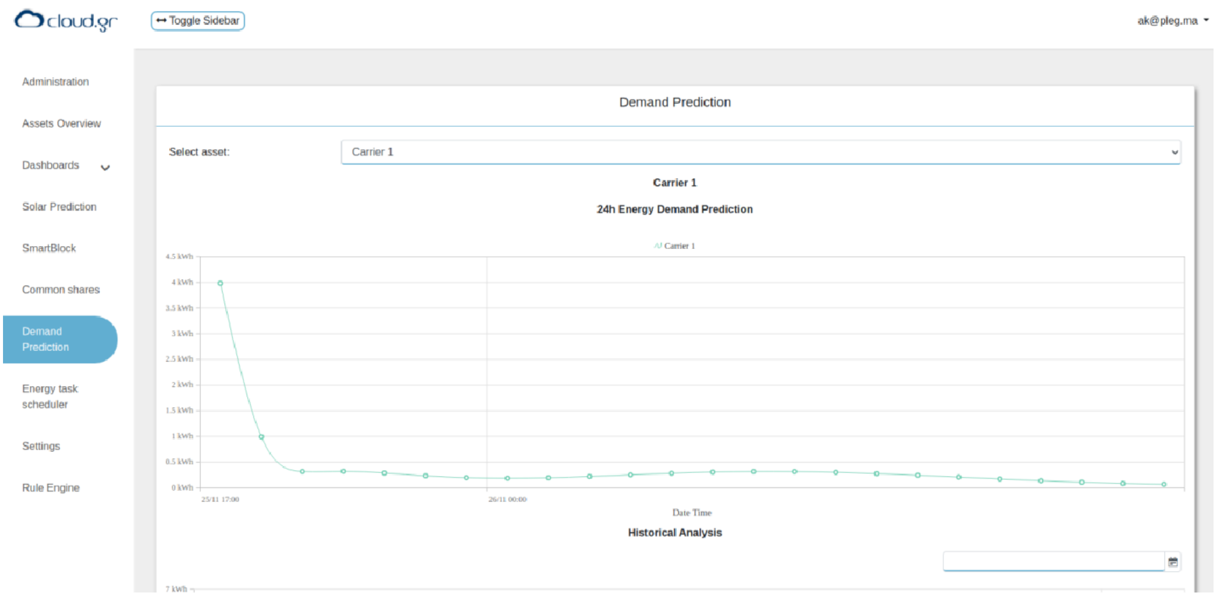


Figure 27: HVAC demand prediction

Moreover, an energy task scheduler module was developed and validated. This component makes green scheduling recommendations for the next day based on the energy generation forecasts of a solar panel installation (Pupin in this example) and based on the schedule provided by the user.

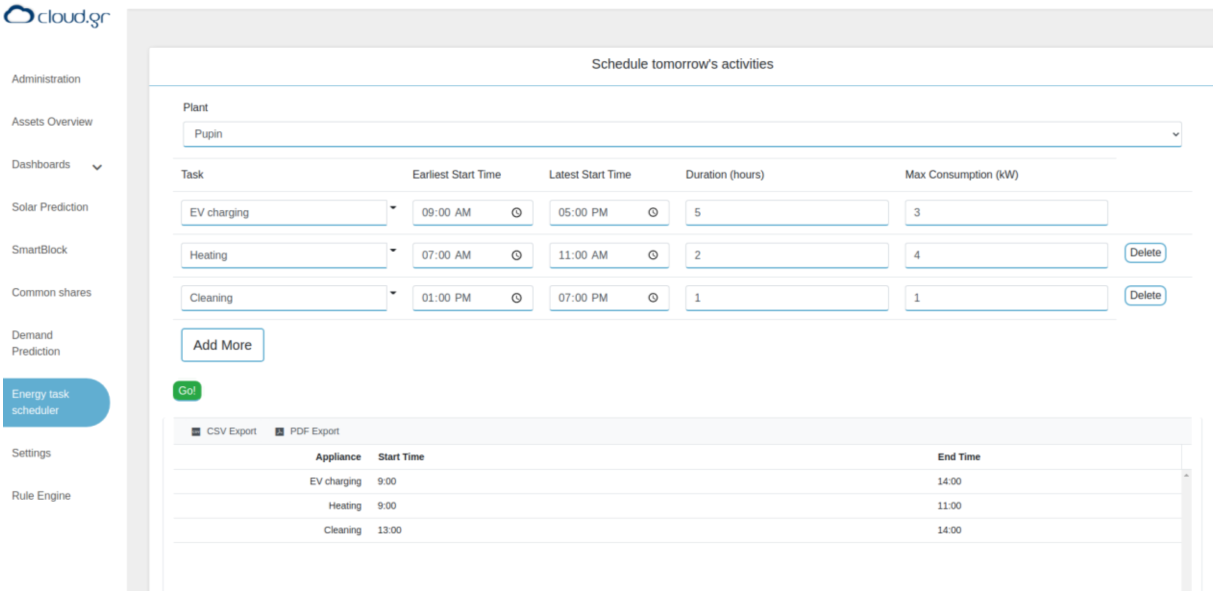


Figure X: Green scheduling recommendations component deployed in PLEGMA's platform

Besides, an air quality forecasting module was developed and validated. This module makes short-term temperature, humidity, CO2, and pm2.5 forecasts for the next 30 minutes using neural networks. These forecasts help energy/building managers to gain real-time insights regarding the indoor air quality of a building, while the deployed system provides recommendations based on the values of the forecasted variables, e.g. good, poor, unhealthy, too dry, too wet, etc. This short-term horizon of 30-minutes is adopted to push energy managers towards taking actions to improve the indoor air quality in real time.

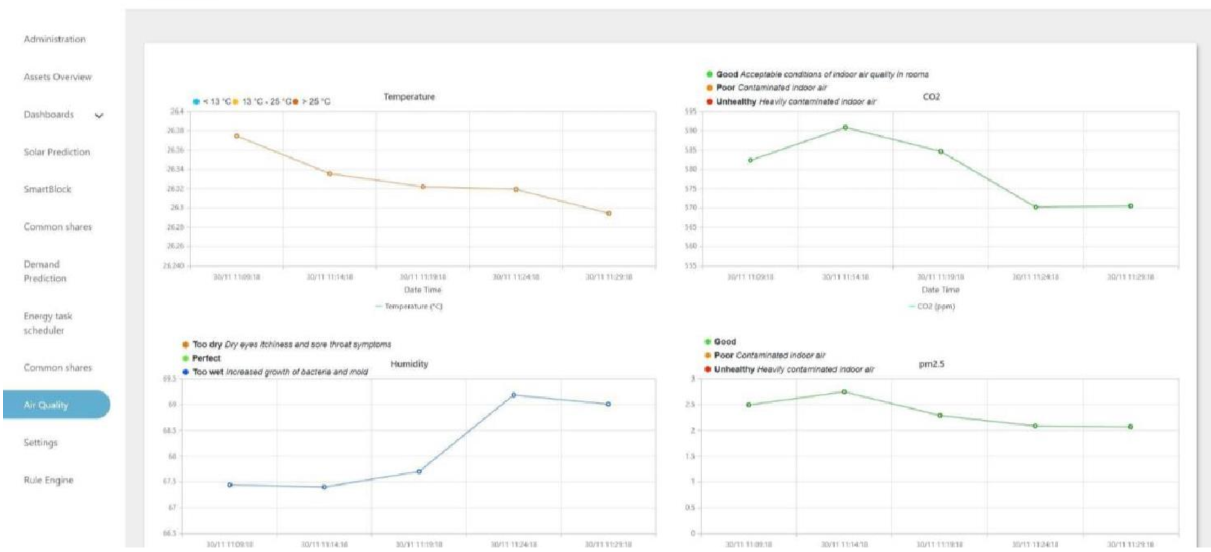


Figure 28: Air quality model prediction

Finally, an IDS connector was implemented, based on Engineering's TRUE (TRUsted Engineering) Connector for the IDS ecosystem, and registered in the PLATOON

Marketplace.Specifically, the developed Plegma Labs platform that is part of the e-PIOTIS project, acts as a data provider in the context of the PLATOON demonstration, by providing forecasts and energy efficiency recommendations to any interested data consumer.

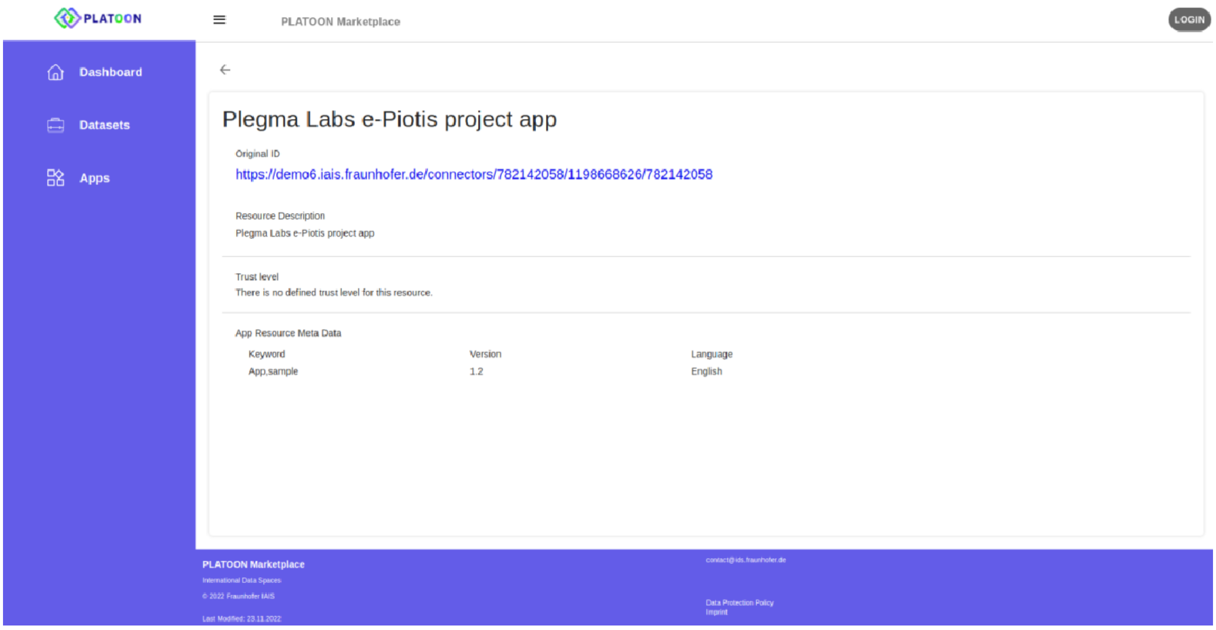


Figure 29: e-Piotis Connector register in the PLATOON Marketplace

3.7.3 Conclusions

The Minimum Viable Product, as set in the Individual Mentoring Plan submitted in April 2022 for the e-PIOTIS project, has been accomplished and delivered on-time.
The results regarding the pilot data collection were analyzed, followed by a description of the components and model pipelines training. Then, the implementation of the data connector to align with the PLATOON reference architecture was described, followed by a presentation of the integration of the EMS microservices of the e-PIOTIS project with the PLATOON marketplace and reference architecture. The integration and deployment of the e-PIOTIS modelling tool components utilizing Docker containerization technology was presented.
Finally, the system prototype validation and refinement through PLATOON pilots feedback was presented, followed by the final system demonstration and evaluation, and a description of the dissemination of the project outcomes through various actions such as a dedicated website, social media, exhibitions etc.

3.8 Enerflow

3.8.1 Objectives

The objectives of the present project were the following:

1. Dockerised code for energy forecasting tool available open source in PLATOON marketplace (priority 1)
2. Data model wrapper through CIM, SAREF, OntoWind (priority 1)
3. Implement and validate dockerised tool in PUPIN's premises (priority 1)
4. Create a secure Jupyter execution environment (priority 1)

5. Implementaparallelforward/backwardfeatureselectionalgorithm(priority 1)
6. Implement an IDS connector (priority 2)
7. Implement an hierarchical load forecasting algorithm (priority 2)
8. Add Rebase Platform in Platoon Marketplace (priority 2).

3.8.2 Results

Enerflow-serve API with functionality for data pipeline, model training, prediction and dockerized deployment was developed and implemented in IMP premises following PLATOON reference architecture and aligned with the defined common semantic data models.
Five different data sources for weather and wind-power production data were implemented. These sources were highly configurable and enable various scenarios where weather and production data can come from different sources. The available data sources were: sparql, MySQL, local files and Rebase Datahub.

The weather forecast benchmark showed that it was possible to improve the weather forecast for some location by combining two or more weather forecast sources. This directly affects the accuracy of energy forecasting (wind/solar power, load, etc) as these quantities are heavily dependent on the weather conditions. The input of the weather prediction model consisted of two weather forecast sources, the ICON and the Unified Model.
Data provided by PUPIN cover the period between June and July 2017 while the reference weather forecasts which were used to compare the results of the model and which are provided by the current weather data provider, covered the period between April 2021 and November 2022. Therefore, there was no possibility to measure the accuracy of the reference weather forecasts. The reanalysis data values which were used instead were the closest possible to the actual values. Two models were trained, one for wind speed prediction and another for temperature prediction.

The temperature forecast accuracy was improved by 24% over the reference forecast using as target the reanalysis ERA5 temperatures as explained in the methodology section. The MAE score over the entire forecast horizon is 1.15 °C while for the reference forecast is 1.51 °C. The improvement was consistent with the lead time as shown in the figures below:

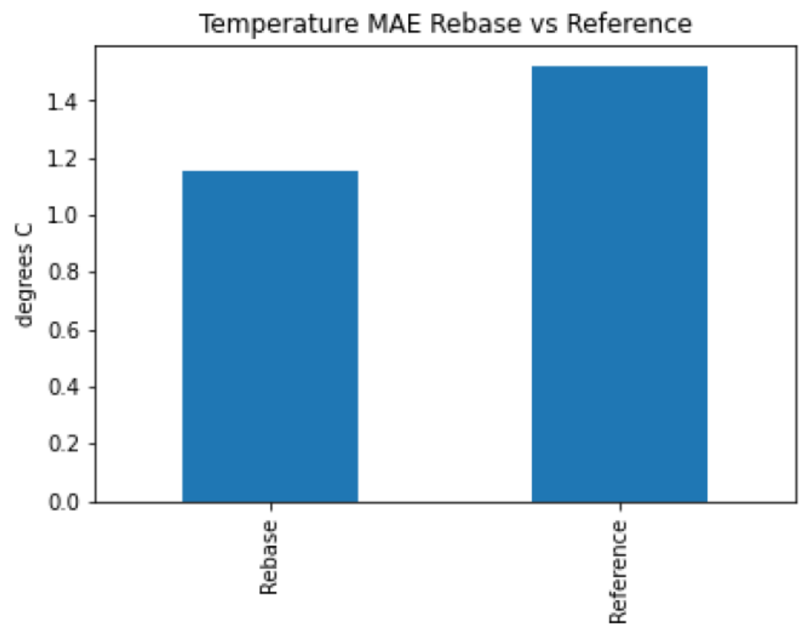


Figure 30: Temperature Forecast - Error score over the entire forecast horizon

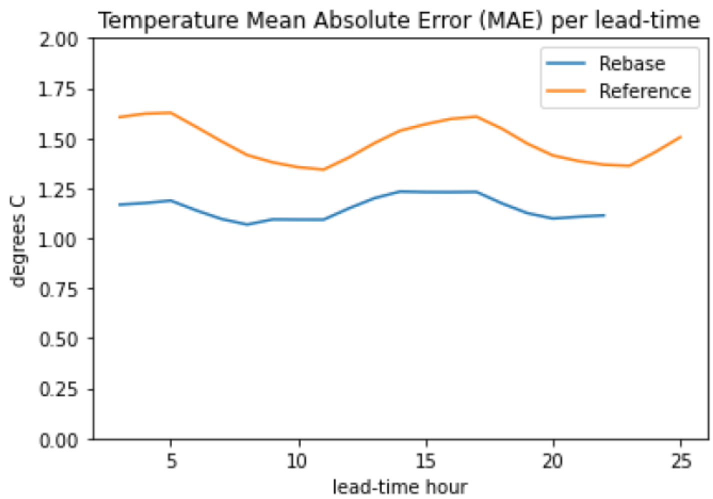


Figure 31: Temperature Forecast - MAE score per lead time hour

The wind speed forecast accuracy improved by 11.46% over the reference forecast. The ERA5 reanalysis wind speed is used as target variable. The MAE score over the entire forecast horizon is 0.55 m/s while for the reference forecast is 0.63. The improvement was consistent with the lead time as shown in the figures below.

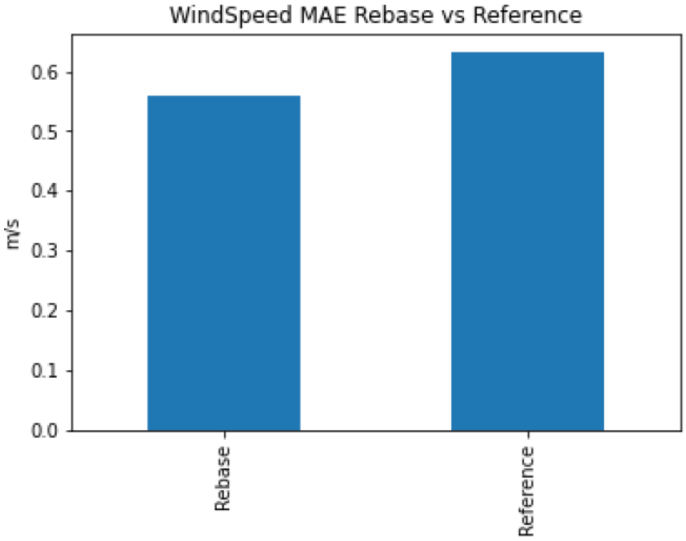


Figure 32: Wind Speed Forecast - Error score over the entire forecast horizon

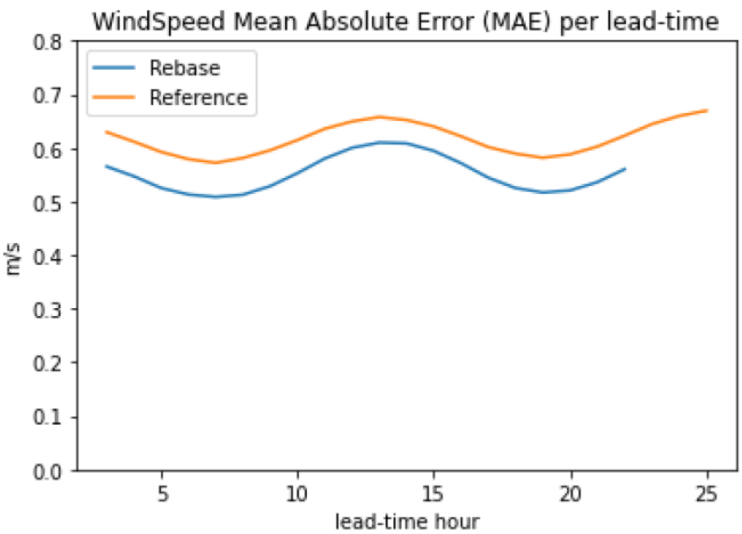


Figure 33: Wind Speed Forecast - MAE score per lead time hour

Finally, the wind power forecast accuracy improved by 18% over the reference forecast. The MAPE score for lead times 12-36 hours ahead (day-ahead) was 6.5% over 8% achieved by the reference forecast. However, it should be mentioned that the reference forecast error score was achieved in a test period which was unknown to us, therefore the results were not directly comparable. However, they provide an estimation of the average error value. The mode shows a small bias towards positive values. No hourly error data for the reference forecast exist.

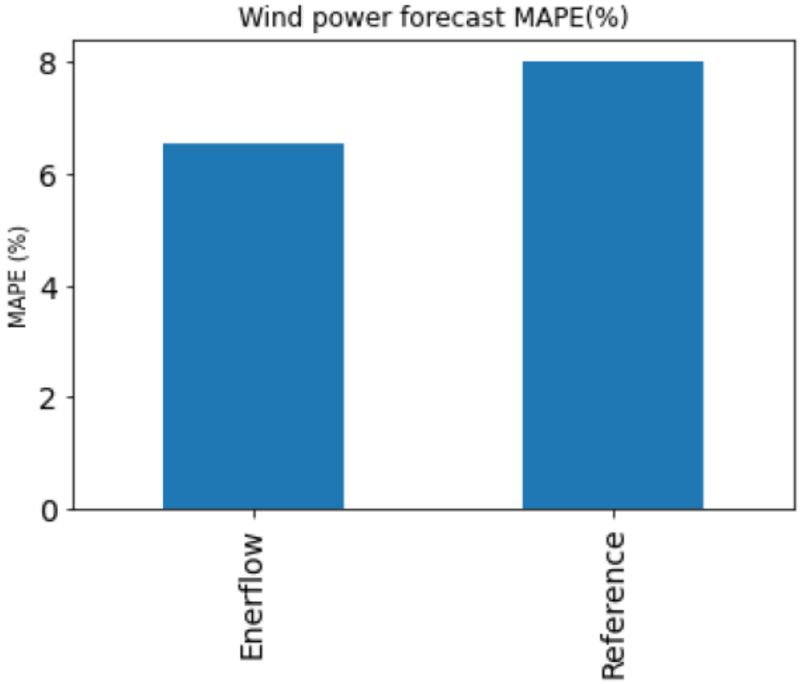


Figure 34: MAPE score for day-ahead forecast

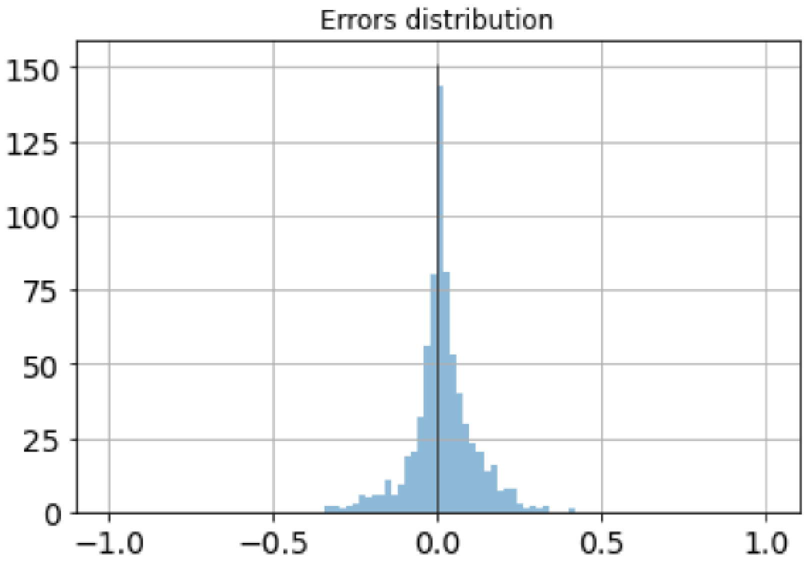


Figure 35: Wind Energy Forecast - Normalised error distribution

3.8.3 Conclusions

The developed wind power forecast tool was successfully implemented in IMP premise integrated with PLATOON architecture.

Two benchmarks were successfully conducted. During the first benchmark we compared the accuracy of the current weather forecasts used by the Krnovo wind plant with the calibrated weather forecasts from the Rebase Datahub. The results shown an increase in wind speed forecast accuracy of 11% and an increase of 24% for temperature forecasts compared to the

reference reanalysis data. The second benchmark compared the Enerflow wind power forecast with the reference forecast and has shown an 18% improvement. However, it should be noted that due to the data scarcity and bad quality, these numbers should be considered as simple references.
Further work could expand the functionality of Enerflow-serve and Enerflow library with additional data sources and various forecasting algorithms. Additionally for benchmarks with more trustworthy results, more measurement data should be collected and cleaned.

3.9 AURORA

3.9.1 Objectives

The objectives of the present project were the following:

1. Interface with the pilot assets through PLATOON compliant architecture and communication protocols.
2. Ingest historical and real-time measurements for all included assets.
3. Perform forecasts using AURORA prediction engines.
4. Assess flexibility potential for all included assets in close to real-time.
5. Perform techno-economic optimization.
6. Generate control signals for optimal use of resources.

3.9.2 Results

For the purposes of real-time data ingestion, a dedicated API endpoint has been developed and deployed to AURORA runtime system. The API uses the same data structure, communication protocol and security measures as the PLATOON instance. This way we ensure:

- Minimal additional development required on the pilot site
- Minimal maintenance needed on the pilot site, since the sending code is the same
- Strong compatibility with PLATOON architecture and potentially other systems

The API endpoint has been secured using

- IP address filtering (only allowing connections from pre-approved pilot IP addresses)
- SSL encryption channel
- HTTP authentication with secure password.

The AURORA's forecasting engine can predict any timeseries data if the appropriate historical dataset is available. The data available from the pilot is consumption and/or production for each asset. Additionally, on-the-fly aggregation of measurements and forecasts is available both through UI and through data APIs. This way, comparisons and analyses can be made without re-calculation. The training of the forecast models is time and resource intensive operation. AURORA's models are re-trained weekly, and the forecasts are built daily for at least 48 hours future window. AURORA's modular structure allows using several different forecasting engines, depending on characteristics and process specifics of each asset type. For the PLATOON assets, the neuralProphet engine was used.

The time granularity of the forecasts defaults to the time granularity of the input data. For easier comparison of the flexibility data, we increased the time granularity of the forecasts to 15 minutes, while keeping 1-minute resolution of the measured data.
The following screens contain visual representation of the forecasted data; the models were built on the 2020 dataset. To accommodate for different seasons, 4 models were trained: spring, summer, autumn and winter.

The results of the forecasts created vary between different asset types. As expected, weather dependent assets, such as PV, can achieve better results. Additionally, these assets also intrinsically operate on regular cycles, which are easily detected and forecasted by forecasting tools. On the other side, the assets which are driven sporadically are difficult to address by forecasting tools. In the next table, we present one set of results for all the assets for September 2020. Assets achieving particularly low error rates were not operational at the given time, therefore their forecasts were trivial.

Table 8: Forecast results - error metrics

ASSET	MAE	RMSE
PLATOON-4A-001	2,69	3,79
PLATOON-4A-002	3	4,24
PLATOON-4A-003	3,1	4,34
PLATOON-4A-004	9,1	10,2
PLATOON-4A-005	10	12,2
PLATOON-4A-006	0,010	0,013
PLATOON-4A-007	1,52	1,91
PLATOON-4A-009	0,073	0,4
PLATOON-4A-010	0,013	0,035
PLATOON-4A-012	4,63	6,06
PLATOON-4A-013	4,62	6,75
PLATOON-4A-014	4,69	6,21
PLATOON-4A-999	1,33	3,99
AVERAGE	3,444	4,626

The following charts depict the best (PLATOON-4A-001 = PV1) and the worst (PLATOON-4A-005 = MicroCHP) predicted assets that were operational at the given period.

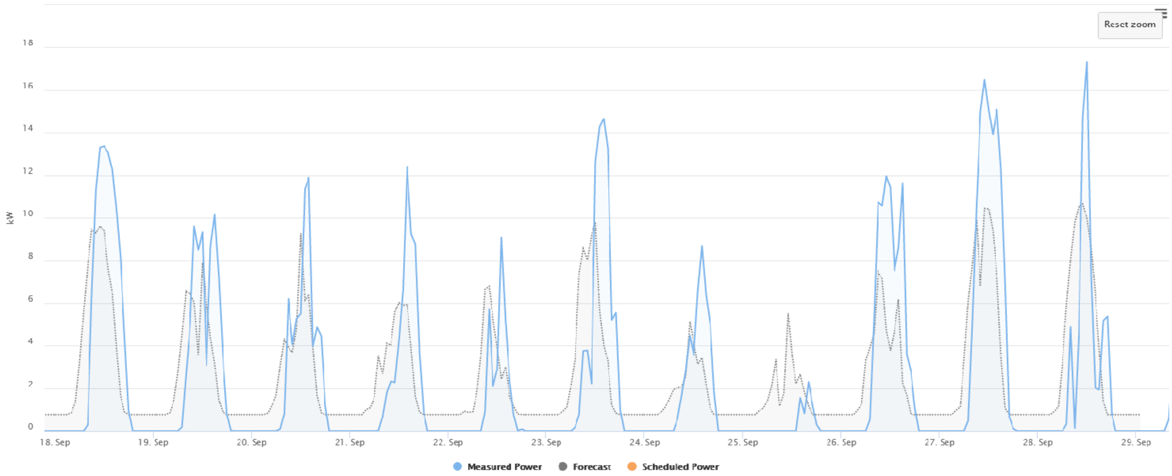


Figure 36: Forecast vs actual value for PV1

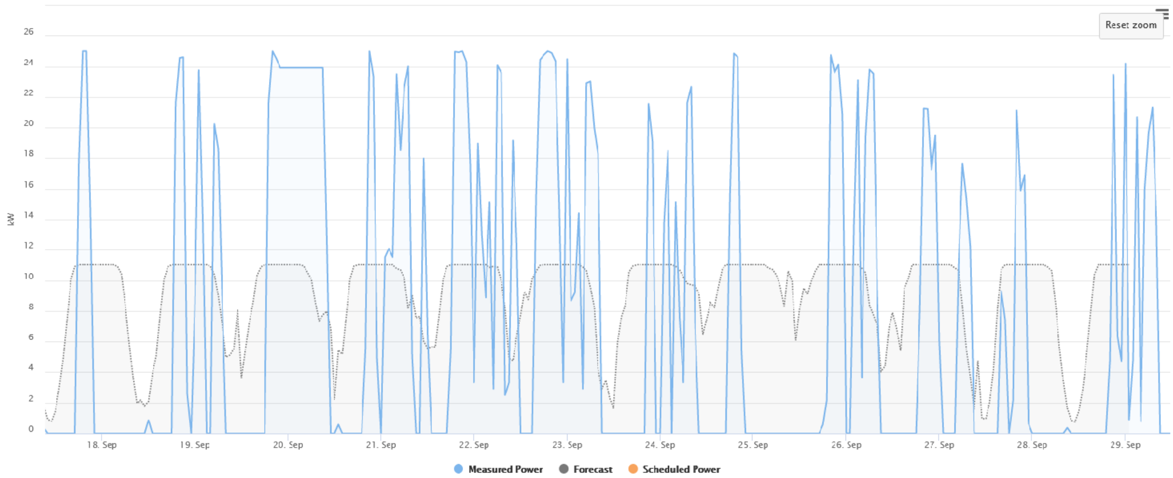


Figure 37: Forecast vs actual value for MicroCHP

In addition, ANODE controller was implemented to monitors assets' operation in order to estimate its flexibility and executes received schedules among other tasks. Deployed and configured were twelve controllers, one controller per asset. ANODE controller consists of more modules (holidays, scheduler, logger, asset controller…). Asset controller is the one which is responsible for flexibility estimation and execution of received energy demand/schedule. First using real time measurements simple forecasts are generated (ANODE controller enables usage of external forecasts as well). Flexibility is estimated based on current asset's operation and predicted future operation. When energy schedules are received asset controller executes them in a closed loop manner. It recalculates adapted energy and adjusts power setpoint to fulfil energy schedule as accurately as possible.

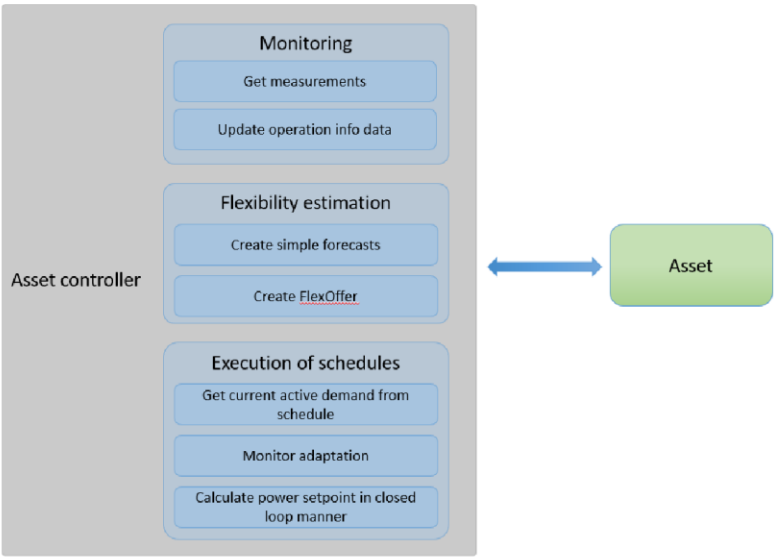


Figure 38: ANODE - Asset controller

Because real time data from the pilot became available only towards the end of the TTP (due to equipment breakdown at the demo site, which is out of RENN's control), historical data from 2020 was used and special real time data simulator was developed. Simulator retrieved historical data from AURORA platform based on the current date and time. Additional noise was added to the obtained measurements. These measurements were available to ANODE controller as real time data. When ANODE controller started with adaptation "power setpoint" and "is intervention" signals were provided to the asset simulator by ANODE controller. Asset simulator followed ANODE's commands only during adaptation instead of using historical data.

Also, a techno-economic optimization through trading was done as depicted in the figure below:

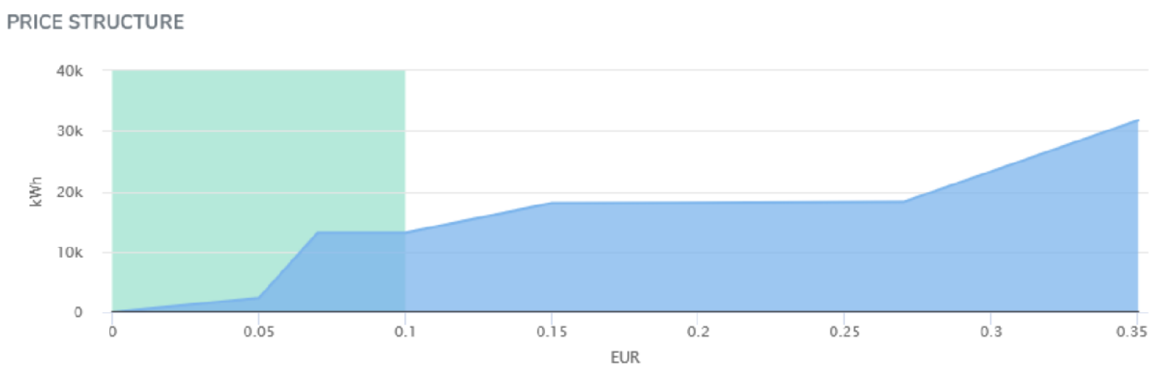


Figure 39: Techno-economic optimization through trading

Finally, a dashboard monitoring screen was developed to visualize live metering data in an aggregated way, depending on the selected focus of the whole system (aggregate changes, based on the focus in the hierarchical structure of assets).

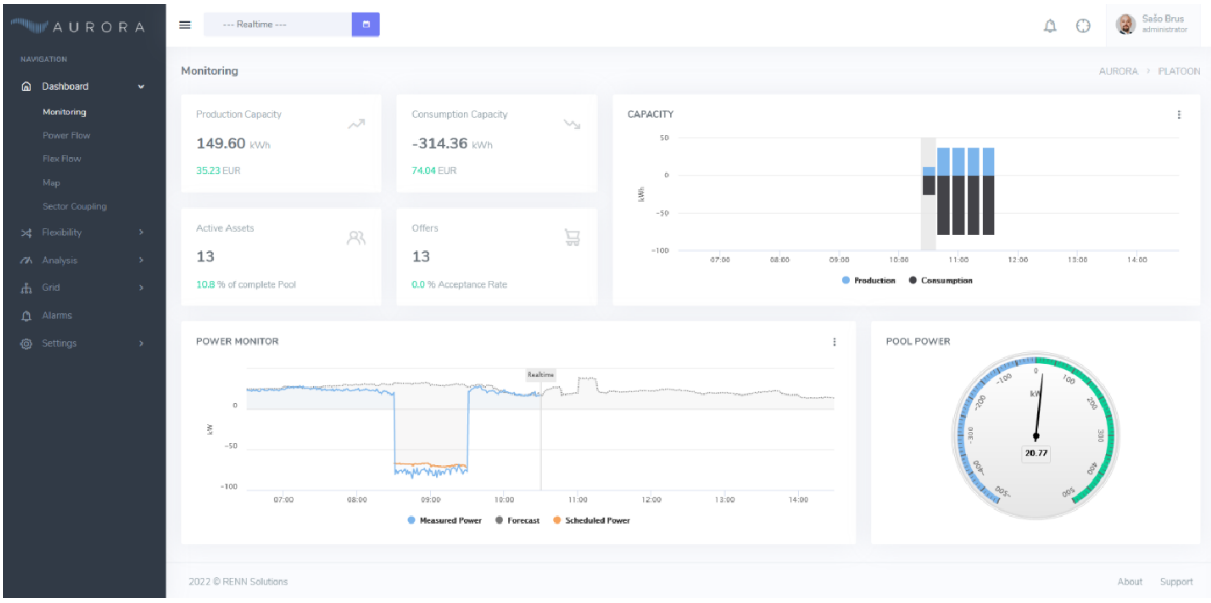
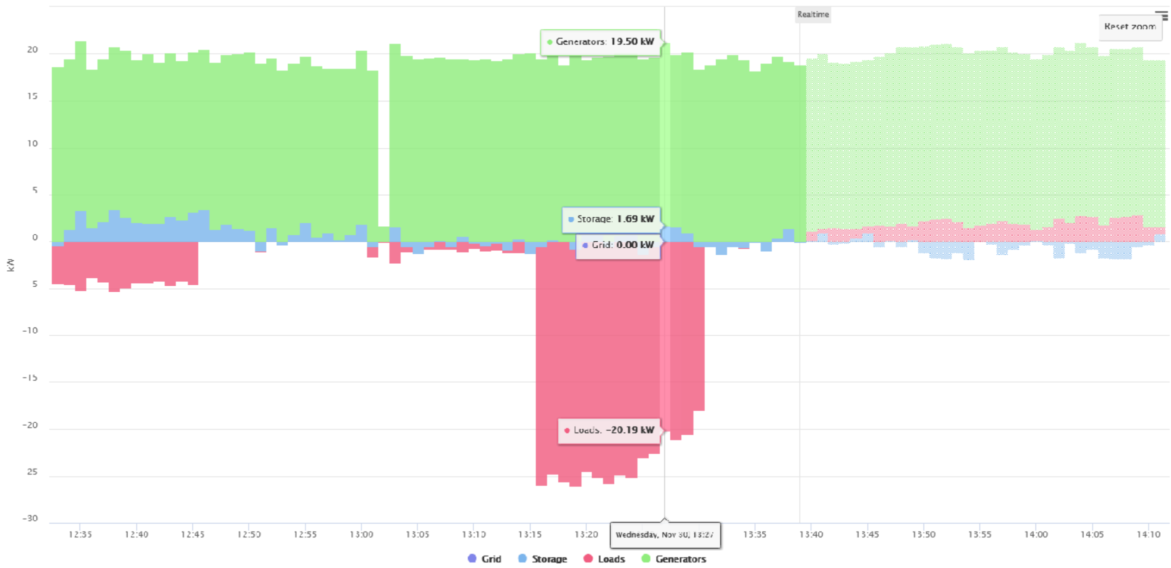


Figure 40: Dashboard with real-time values

In the screen below, we can observe the imbalance in the shape of over-generation (left side). In the activation window (center), AURORA was able to find a better match between generation and consumption – in this case the system instructed to increase the load, which resulted in an almost balanced system. After the activation window (right side), the load decreased, and the imbalance returned. In real operation, such a use case would run continuously, assuring balance in the (sub) system.



3.9.3 Conclusions

All the tools defined in the individual mentoring plan were successfully implemented and validated. In fact, a system operation analysis that goes beyond the required objectives was performed proving interesting insights. The response behavior is modelled and is based on the same model parameters that define PLATOON assets. This way we can test aggregated and individual response of the assets as well as AURORA's benchmarking functionality without interfering with actual operation.

Different potential improvements for further work were listed regarding forecast, asset inclusion, dedicated processing nodes for forecasting and dataset cleaning.

3.10 Heliocity

3.10.1 Objectives

The objectives of the present project were the following:

1. Assess and monitor (continuously) the performance of the 12kWc solar system installed on top of the nanoGUNE building in San Sebastian, Spain.
2. Test how Heliocity core algorithm (virtual sensor) can replace temperature and irradiance outdoor sensors on top of the nanoGUNE building in San Sebastian, Spain.
3. Develop a MVP fully compliant with Platoon project reference architecture, including IDS and Semantic interoperability on nanoGUNE building in San Sebastian, Spain.

3.10.2 Results

A fully functional front end was developed for the PV performance monitoring tool, using the Vue JS framework interfaced to a dedicated FastAPI backend. The function of the backend was to authenticate connection requests and provide a series of API routes to serve the various tabulated and graphical representations of data on the frontend. True to its purpose as a performance analysis tool designed for an expert operator, the front end was designed to present results in a hierarchical manner: the description information to configure the analytics applications is prepared by the client by completing standard template files.

A data gateway was developed for an end2end integration of the performance assessment tool and the pilot site database server. This gateway was activated on a daily basis to recover the previous days of performance data. Once the data had been received and converted to the internal format of the Heliocity application, the performance analysis tool was launched on the most recently available data. Results were then automatically posted to a dedicated database ready for consultation on the front end.

To allow a continuous service for PoC#2 (Virtual sensors), Heliocity core algorithm required substantial modifications to be able to infer environmental conditions from performance results rather than its initial function that was to do precisely the reverse operation. The adaptations necessary for the performance monitoring tool were also introduced for the virtual sensor, which was constructed as an extension to the performance analyser.
The virtual sensor application works by analysing recent historical performance and weather data, before projecting a model for the current day where only production data are available. The application was designed to be launched multiple times per day (in tests it was operated on an hourly basis). The output of the virtual sensor is a set of tabulated results for the current day, including inferred solar radiation and ambient temperature. These results are then consulted by an API route that allows a user to consult the most recent virtual sensor readings.

In the following figures, estimations of solar radiation by the two references are shown superposed with the prediction from the virtual sensor, for the months of June and July.

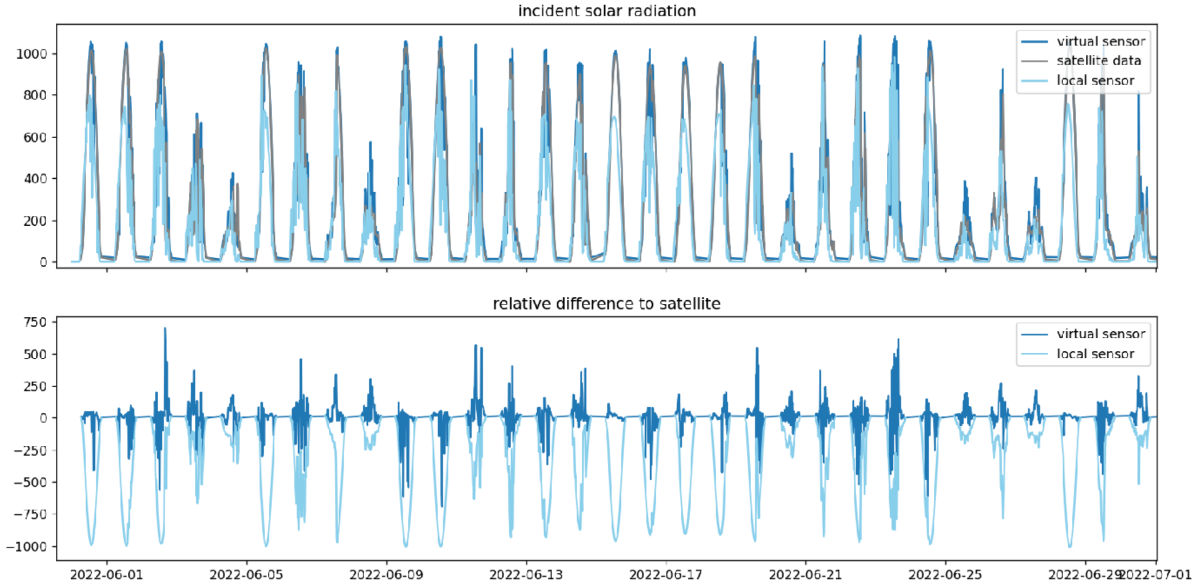


Figure 41: Virtual sensor predictions of solar radiation compared to local sensor and satellite data in June 2022. Top: Absolute solar intensity estimates. Bottom: Difference between satellite intensity and other sensors

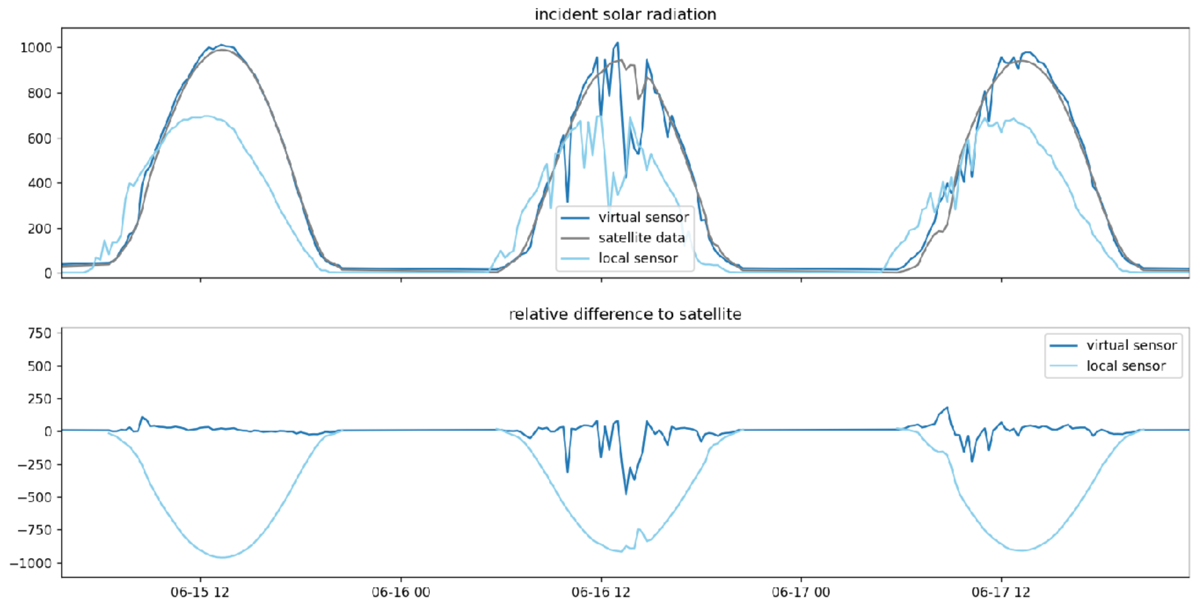


Figure 42: Virtual sensor predictions of solar radiation compared to local sensor and satellite data, zoom for June 2022. Top: Absolute solar intensity estimates. Bottom: Difference between satellite intensity and other sensors

As per typical operation, the algorithm was trained on data covering a period of 30 days each time. For this interval, although the absolute values of the local sensor are spuriously low, the two references are qualitatively consistent with similar episodes of extended sunshine or cloud cover. For short term variations, the local sensor exhibits considerably more fluctuations than the satellite data, as expected due to the averaging effect of satellite data retrieved for an area of several square kilometres.

The results of the virtual sensor predictions for ambient temperature are shown in the following figures for the months of June and July, compared to off-site weather services (satellite) and a local temperature sensor.

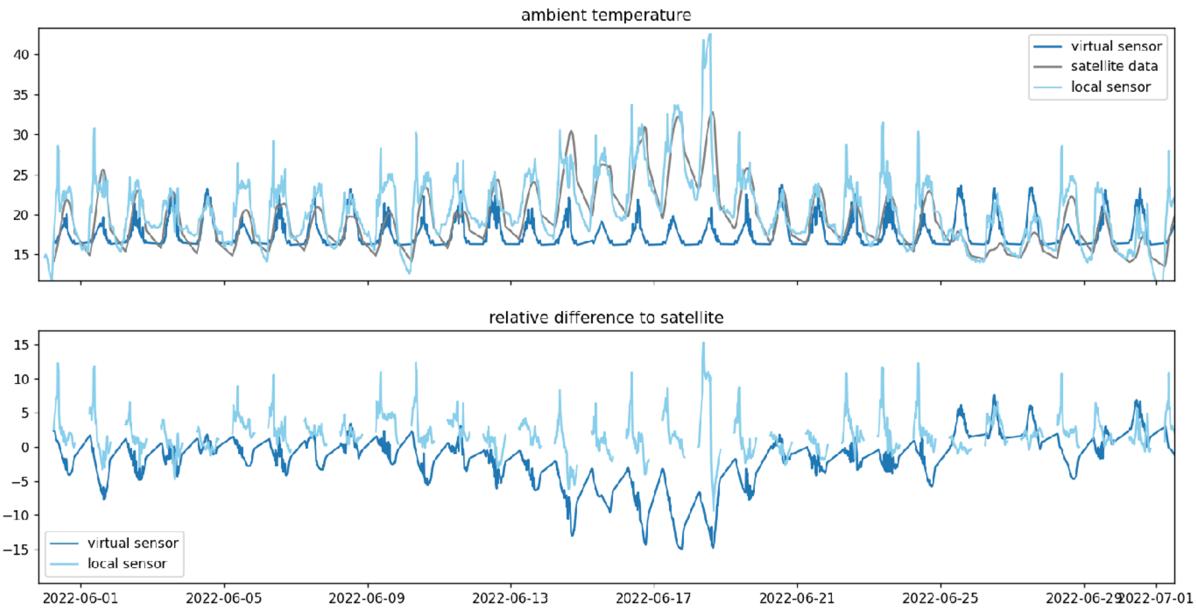


Figure 43: Virtual sensor predictions of ambient temperature compared to local sensor and satellite data in June 2022. Top: Absolute solar intensity estimates. Bottom: Difference between satellite intensity and other sensors.

Compared to the two references, the ambient temperature virtual sensor appears somewhat unreliable.

For the interval shown in the figure, the difference between virtual sensor and references is of order 5°C. However, given that variations between the local sensor and satellite data of the same order of magnitude were observed, with peak discrepancies exceeding 10°C, the quality of the method is relatively high.

The virtual sensor presents the apparent thermal variation according to the power plant behaviour. The supposed anomalous variations in the virtual sensor predictions are also due to uncertainties in the theoretical model that was used to calculate expected system performance as a function of satellite data, and served as an input for the training model. The virtual sensor values therefore reflected a combination of these two inputs.

A site visit was carried out in June 2022 with the aid of representatives of the pilot project. During this site visit, several observations were made that corroborate the hypothesis that the thermal state of the PV array was poorly correlated to ambient temperature measurements.

The PV panels were confirmed to be positioned 5m above rooftop surface, above HVAC chillers and Ventilation inlets and outlets. Fencing surrounding the installation likely limited the effect of wind over the array, and conditions were noticeably not windy during the visit.

Substantial mechanical ventilation outlets were observed to direct building air directly onto the PV modules. A clean room air outlet (labelled corrosive) provides a near continuous stream of air at 20°C to 2 modules on one row. Additionally, the building energy management system

is understood to rapidly renew the building air in the morning and may also operate punctually.
Two temperature sensors were identified during the site visit: one sensor is located at the main HVAC inlet, the other is a housed weather temperature sensor, positioned on the frame at the east/west limit of the structure.

The fully functional end-to-end demonstrators explained above were reconstructed upon an IDS architecture in order to fulfil the final objective of the project. The key differences between preceding continuous services and the IDS-based services are illustrated in the diagram below, which shows the main features of IDS connectors and data processing. In this case the Data Space connector from Fraunhofer was implemented.

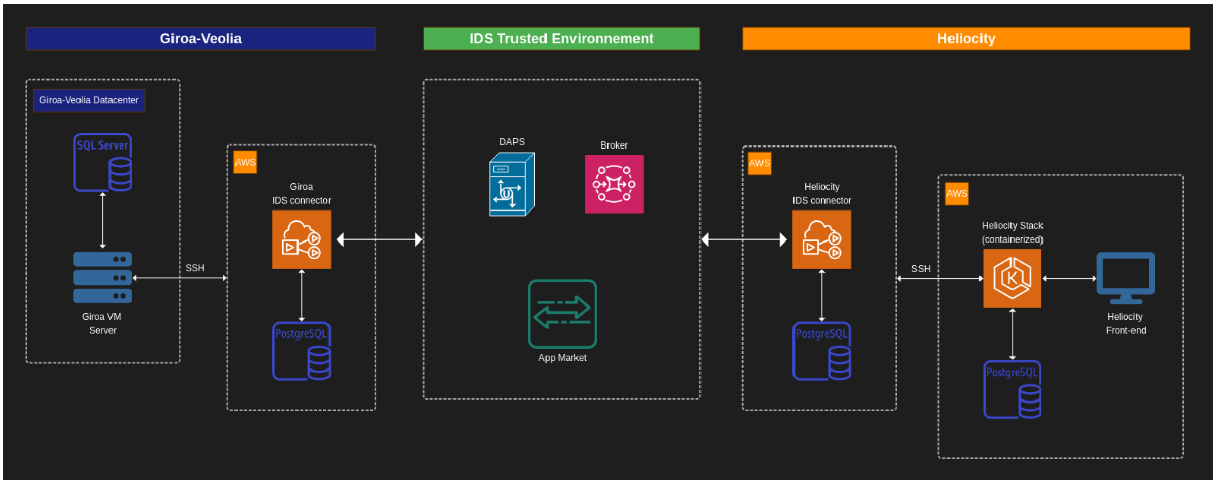


Figure 44: Fully functional IDS compliant end2end demonstrator architecture diagram

It is to be noted that in order to secure the on-time availability of the end2end demonstrator, the Giroa IDS connector was deployed onto an AWS server under Heliocity subdomain.

3.10.3 Conclusions

All the components defined in the Individual Mentoring Plan were successfully implemented and validated.
Regarding the solar radiation virtual sensor showed to be adequate alternative to local sensors, and provides finer short-term information than satellite data. Regarding the feasibility of estimating ambient temperature by a solar plant virtual sensor, the study applied to the pilot project was inconclusive. In its current form, the ambient temperature estimator cannot be recommended as an alternative to local sensors, at least in this specific environment.

3.11 Venera

3.11.1 Objectives

The objectives of the present project were the following:

1. To build a scalable hardware-software system for Energy Consumptions near-real-time data acquisition from energy meters in buildings belonging to Roma Capitale Pilot (·B-ROM).

2. To create customer engagement and an easy-to-use workflow which satisfies Roma Capitale needs and requirements in terms of energy management system (EMS).
3. Bring all the frequency-normalized (e.g. 15 minutes) data on a unified dashboard.

3.11.2 Results

Several meters were installed in a large number of buildings in a short time following an efficient and scalable methodology. Two types of hardware were set up for data acquisition:
• Invasive Kit characterised by a physical installation that included work on the building's electrical panels.

• Non-Invasive Kit characterised by an installation without intervention on the building's electrical panel using Smart Meter Open Protocol (Chain 2).

The procedure adopted was different according to the different types of installation; specifically, for the invasive installation it was necessary to involve Installation technicians; Building referents for organising the inspection and installation date and Specialised installation company.

During August 2022, Venera Team installed two invasive Kit in two building. During October 2022, Venera Team carried out the inspections of the remaining buildings, after the inspection Venera Team understood that of the twelve planned buildings, only ten could be properly installed through non-invasive kit, because the other two were not of interest to the Municipality of Rome (not managed by the municipality's technical offices). During November 2022, we carried out the installation of the identified buildings. The second batch of installation was composed by building with Smart Meter and Chain 2 protocol.

Also, Venera Team, considering the cost to scale the solution to the whole set of Building, defined the data acquisition strategies for Bulk Upload of Thermal and Energy data. The team discovered that Gas and Thermal Counter Data could be acquired through CPL / eFM that are the dealer for the GAS metering part. Regarding the Energy Data the Energy Provider share every month a report with every meter consumption, so starting from this data the company implemented an acquisition flow to visualize and share those data with the Digital Enabler.
The Real Time Edge Device (in both versions: Energy Meter and Chain 2) will send data to the Digital Enabler through the IoT Connector.

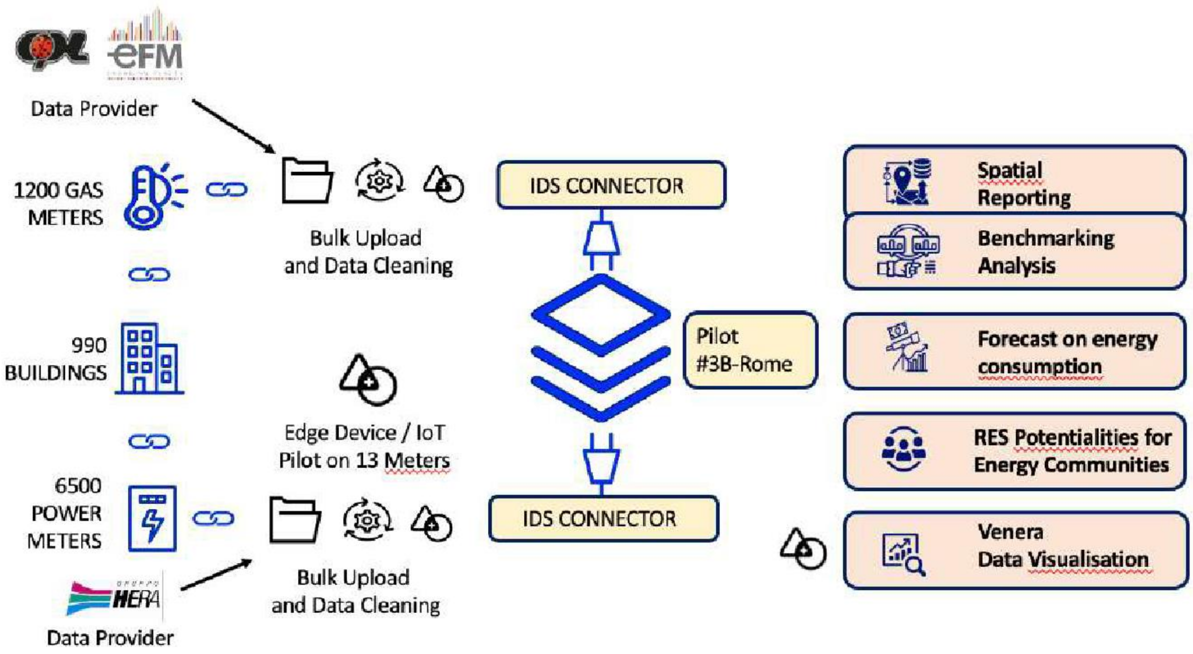


Figure 45: ICT architecture

In addition to the implantation of the IoT data stream for the electricity meters, two data acquisition and information sharing streams were set up with the platform in massive mode to overcome installation limitations. More specifically:

- THERMAL DATA: Data will be acquired through an integration with CPL Concordia / eFM data infrastructure. This integration will be detailed under the "Integration Analysis" paragraph in this deliverable.
- ELECTRICITY DATA: The electricity data will be acquired through IoT Sensors, Edge-Device or Devices that communicate with the Chain 2. We have developed two type of IoT Kit to implement the data acquisition. We also have the opportunity to integrate monthly data through Gruppo Hera.

The ambition of Venera project is to set up the automatic flow of data acquisition, while for Thermal and Electrical meters Data there is monthly data availability (providers: CPL-eFM and Gruppo Hera), for 2400 thermal sensors already installed hi frequency data are collected, but unfortunately there is no real-time data flow.
For this reason (real-time data), we need to create Hardware Kits composed of sensors to acquire data from the field, in our project we are focused on General Energy Meter Data. The Kits that we will install are:

- Chain 2 Kit: Non-invasive installation that acquires Data from Smart Meter 2.0.

Energy Meter Kit: Invasive Installation that acquires Electricity Data through certified Energy Meters. The installation of the new smart meter 2.0, that will be installed everywhere in Italy by 2024 (at the moment it is installed in several meters in Italy), provides the end user with the possibility to receive, store and use electricity data in real time in a totally open way. This is possible thanks to the Chain2 communication channel that is offered by 2G electric meter, this communication channel doesn't need any installation but only a plug and play device called User Device. The device communicates with the IoT Architecture:
• Real-Time Energy and Power Data.
• Alert for exceeding the power supply.

The Chain 2 kit is equipped with a Cellular Modem to have an independent communication channel with respect to the Rome capital infrastructure.

Figure 46: Real Time Edge Device

All these data were integrated with the Digital Enabler platform provided by ENG. The figures below show the dashboard with some project related KPIs such as the number of assets, connected assets and current anomalies, as well as a map of the geo-located assets.

fig...

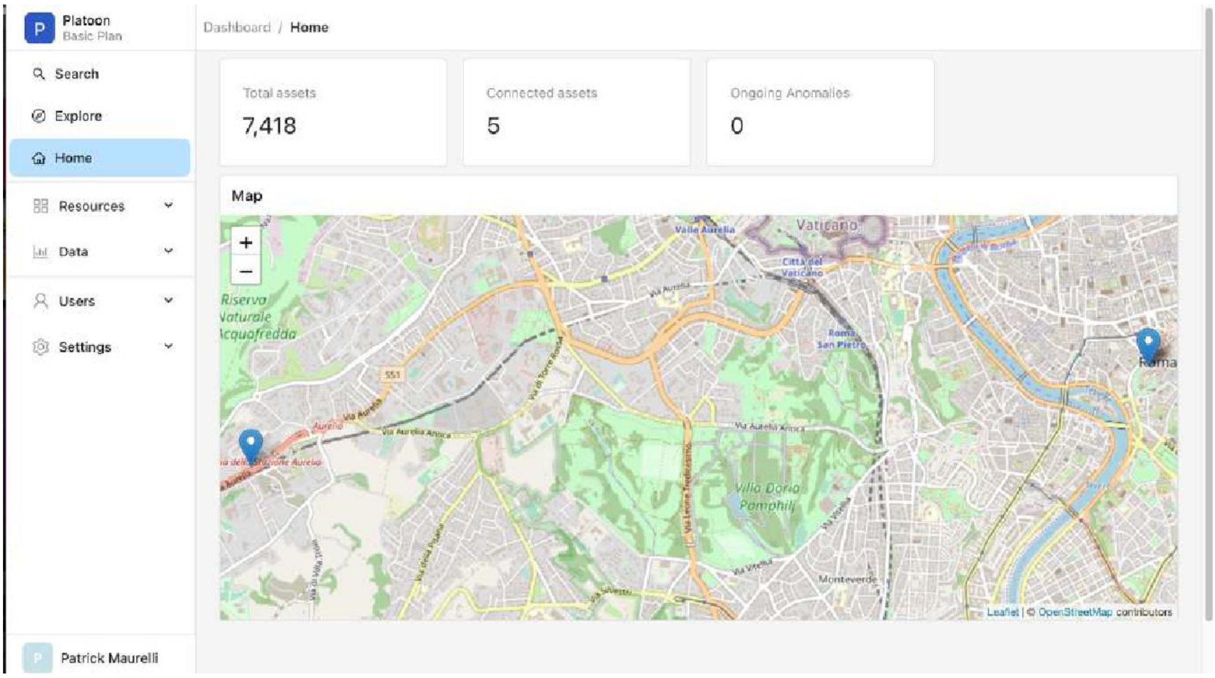


Figure 47: Venera IoT Dashboard – Geo Location

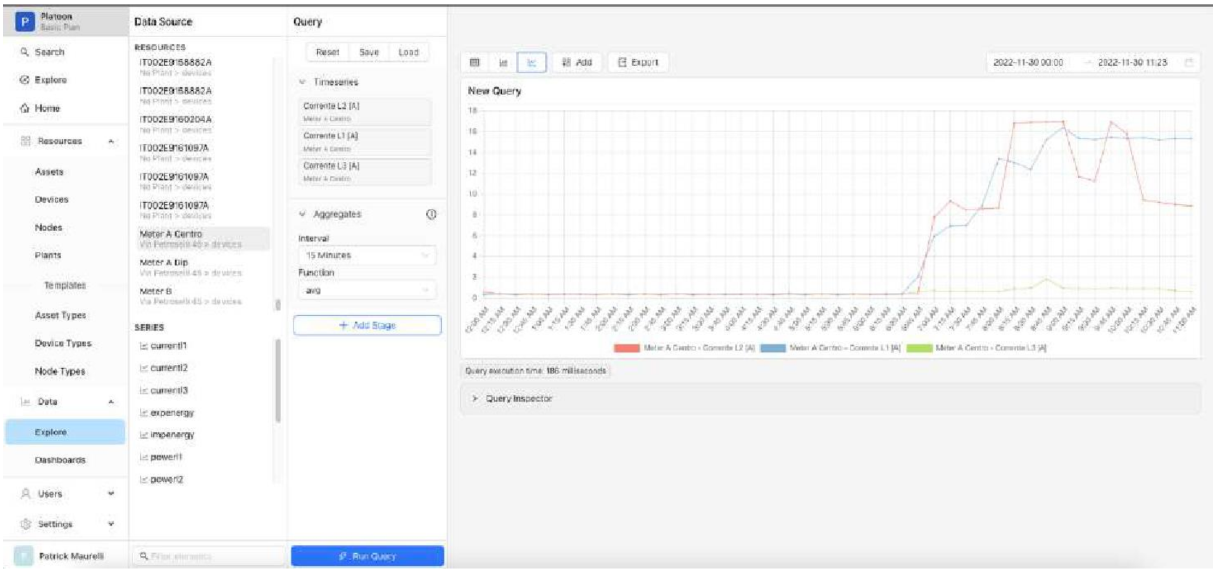


Figure 48: Venera IoT Dashboard – energy consumption data

In the figure below we have an overview of production-oriented data. For instance, in the case of Photovoltaic Plants, we have solar irradiation, produced energy, exported energy and other KPIs such as the Performance Ratio.

Figure 49: Venera IoT Dashboard – PV energy generation

3.11.3 Conclusions

Most of the IoT sensors defined in the Individual Mentoring Plan were installed. Some of them could not be installed due to access to the facilities. Also, some new real-time energy meters were tested using Chain 2 protocol that will be fully available on building by 2024. All the measured data was integrated in Digital Enabler platform for subsequent analysis using the data analytics tools developed in WP4. l

The team also carried out an economic analysis concerning the scale-up of the platform and approaches on all buildings. Given the installation costs and possibilities, the following strategies are also economically feasible.

For the Energy Managers' activities, the integration of monthly data within the Digital Enabler by fully activating the automatic acquisition flow supported by CPL-eFM (Thermal Data) and Hera (Electrical Data) data allows observability on general consumption.
Advantages of this approach:

- No Installation Costs
- No Hardware Costs

Disadvantages of this approach:

- No Real-Time Update
- Only Monthly Data, in some cases weekly (at the moment HERA and CPL don't send quarterly data)

For PV maintenance and PV management the Energy Meter Kit and Venera PV dashboard enables an advanced management capabilities. This approach is very useful for PV because there are only 167 PVs so installation and hardware costs are feasible.
Advantages of this approach

- PV Management
- Anomaly Detections on PV
- Detailed Report
- Real – Time Data and Notifications

Disadvantages of this approach

- Installation Costs
- Hardware Costs

To implement Ancillary Services like Demand Response or Energy Communities, the Chain 2 Kit could be used. The Chain 2 Kit is very useful because could be adopted in a scalable and affordable way and enables a data flow that is certified (Smart Meter data).
Advantages of this approach

- Anomaly Detections
- Real – Time Data
- Energy Communities Data Management

Disadvantages of this approach

- Hardware Costs

3.12 INvolving hydrogen for a GReener and Innovative energy Deployment

3.12.1 Objectives

The objectives of the present project were the following:

1. Identification and characterization of the dynamic loads of the facility served by the micro-grid, along with the main technologies related to hydrogen/renewables electricity generation.

2. Development and validation of digital twins able to reproduce the dynamic performances of:
    - cogeneration engine fuelled with H_2/CH_4 mixtures;

- solar PVs;
- electric storage systems;
- H2 storage systems;
- other H2-fueled systems for electric production, e.g., fuel cells.

Definition of performance maps of each component, to be given as Open Data to the PLATOON Reference Platform.

3. Development and validation of a digital twin of the complete layout which fulfils the identified electrical, heating and refrigeration loads over an annual period of operation. These lasts will comprise further electrical loads deriving from EVs connected to the grid. The digital twin will serve to identify the optimised layout that can lead to advantages from the technical, environmental and economic point of view. Definition of data sets to become Open Data for the PLATOON Marketplace.

4. Interface with the pilot assets through PLATOON compliant architecture and communication protocols.

5. Embed historical and real-time measurements for the considered assets.

3.12.2 Results

ICEs Performance Maps of an ICE-CHP when fuelled with mixtures of NG and H2 at different percentages in volume were developed. These data maps are suitable for various uses, to predict electric power and heat generation in any application of possible interest. As an example, that is here provided, the map relevant to the TOTEM25 cogeneration unit of the POLIMI microgrid, it is a fundamental tool to describe the CHP performances for PLATOON Pilot #4A.

The development and validation of each of the energetic components of Pilot #4A was done. The technical feasibility of multiple energy source integration was estimated by comparing the dynamic performances over a whole year against energetic loads from the University Energy Balance of POLIMI.
Different control strategies and layouts were considered, as by varying the scheduling working hours of the cogenerate engine, the capacity of the electrical storage system or the possibility of employing green hydrogen for electric production through blended fuel operations.

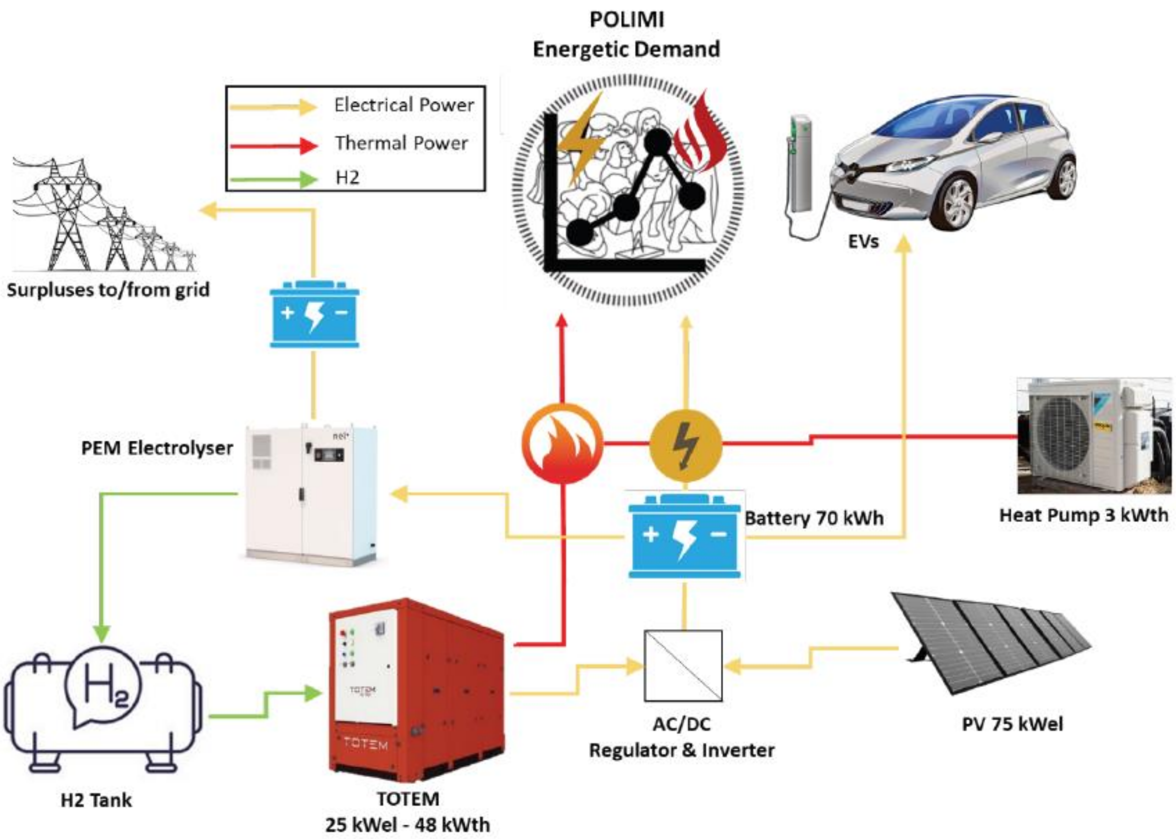


Figure 50: Scheme of the modelled POLIMI microgrid

The figures below represent the comparison between the demanded and produced energies on a monthly basis for both the electrical and thermal loads, when the ICE-CHP works during all the 8760 hours of a year (Case 1.a) or just during the night (Case 1.b) from 18.00 to 8.00. During the winter months (November to March), the Case 1.a strategy leads to an electrical and thermal production almost simultaneous with the demanded one, limiting any energetic excesses. This result is more clearly shown in Figure 9.a where the power demands and productions are reported on an hourly basis.

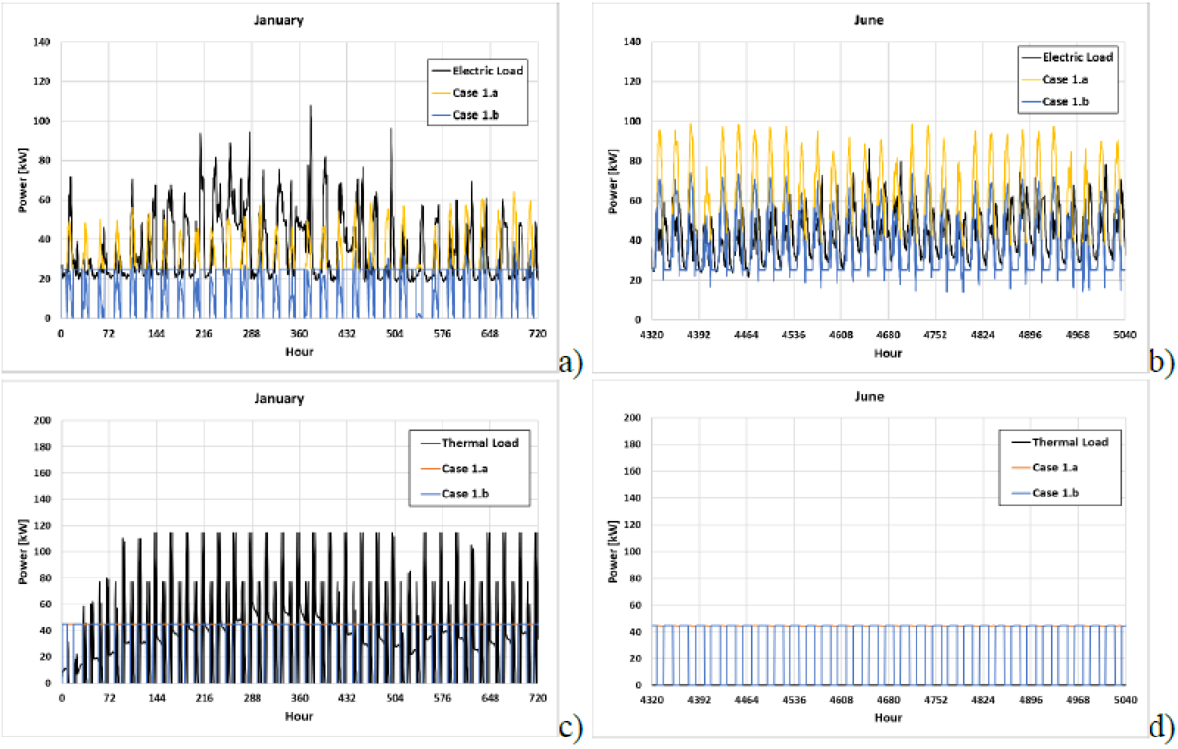


Figure 51: Electric load (black), electric production Case 1.a (yellow), electric production

An economic and environmental analysis of the results was performed. The economic analysis includes the calculation of the Life Cycle Cost Saving (LCS) and the Payback Time (PBT), which are determined by considering the system capital cost, as well as operation and maintenance costs. The cost savings are calculated with respect to a reference case in which natural gas is purchased to be used in a boiler for heating purposes and electricity is taken from the grid to match the energy demand. The LCS represents the total energy cost savings over the supposed system lifetime and is calculated through the following formula:

$$LCS = \left(\frac{C_S}{d-i_f}\right)\left[1-\left(\frac{1+i_f}{1+d}\right)^n\right]-C_0$$

Table below shows the results of the economic analysis reported over an assumed system lifetime of 10 years revealing an LCS that goes from 770,02 k€, for Case 1.a, to 189,2 k€ in the Case 1.b, with a PBT shifting from the previous 0,62 years to 2,42 years. The O&M costs are lower in Case 1.b by virtue of the lower NG consumption associated with the ICE operation.
Furthermore, the proposed layout under Case 1.a leads to a reduction in CO2 emissions of 129,72 ton/year compared to the 94,8 ton/year of Case 1.b, thus also decreasing the related environmental penalty costs.
Lastly, during the Case 1.b strategy operations, less power produced goes to cover the electric demand, thus also reducing the amount of hydrogen to be sold as less excesses are destinated to the electrolyser.

Table 9: Comparison between the economic and environmental parameters defined when Case 1.a and Case 1.b management logic are implemented.

Parameter	Case 1.a	Case 1.b	Percentage Variation
C_0 [k€]	455,15	455,15	-
$C_{O\&M}$ [k€]	9,53	7,43	-22,0%
C_s [k€]	108,58	57,1	-47,4%
LCS [k€]	770,02	189,2	-75,4%
PBT [year]	0,62	2,42	+290,3%
ER_{ng} [ton_{CO2}]	12,26	9,29	-24,2%
ER_{el} [ton_{CO2}]	117,45	85,51	-27,2%
ER_{tot} [ton_{CO2}]	129,71	94,80	-26,9%
EPCS [k€]	102,45	74,88	-26,9%
TCS [k€]	211,0	131,99	-37,5%
Demanded [MWh]	301,9	301,9	-
E_{cov} [MWh]	252,1	214,8	-14,8%
E_{exc} [MWh]	83,5	29,9	-64,2%
Q_{cov} [MWh]	48,8	36,9	-24,4%
H_2 excesses [kg]	271,5	80,2	-70,5%

3.12.3 Conclusions

Present work was dedicated to the development of performance maps of ICE-CHP units suitable to provide useful data for energy management also under NG-H2 fuelling operations. The developed tool was first derived for the TOTEM25 engine mounted in the Pilot #4A of the Project, then generalised also for other engines of various sizes of power. The performance maps were released in .csv format, so to be converted in JSON format and easily integrated in the PLATOON Reference Platform.

The development of a numerical model of the complete microgrid belonging to the POLIMI University was also performed, composed by energy generation and storage technologies that are part of the PLATOON Pilot #4A. Specifically, the numerical model was applied to study the influence, over the technical, economic and environmental performances, related to the implementation of several energy management techniques (Strategies). These lasts derived from the definition of a proper DoE, where main parameters were modified in both a qualitative and a quantitative way.

Among the solutions proposed in the first three scenarios, the one belonging to Scenario 2, where the ICE-CHP is fuelled with mixtures of NG-H2 for 8760 hours in a year resulted as the most convenient from both the technical (84% of the produced power is destined to cover the energetic demand), economic (PBT of 0.58 years, avoided costs equal to 217 k€) and environmental (132 ton/year of avoided CO2) point of view. This scenario was also then applied to study performances when the energetic load associated to EV charging is varied in time and in value. The results showed how the variation of this parameter slightly influences the overall performances.

Lastly, the tools were implemented as Cloud services (as AWS) integrated with the PLATOON federated platform ensuring the Interoperability and data security, sovereignty and privacy aspects.

3.13 High Resolution Demand Profiles for Transformer Digital Twinning

3.13.1 Objectives

The objectives of the present project were the following:

1. Improve LV/MV transformer monitoring by 10-20% through better demand modelling. This methodology is currently under pilot with a UK Grid Operator providing strategic decision-making tools for 2 million buildings saving up to €19 million/year in grid reinforcement costs.

3.13.2 Results

The project integrated the IEC60076 thermal into a digital twin that was able to successfully predict the oil temperature for the pilot location transformers.

The raw data obtained from the SAMPOL included information on transformer load, top oil temperature and the weather data. Additionally, a datasheet was also provided which was then used to extract the parameters/specifications about the transformers such as the oil volume, kVA rating etc.

The essential data required for the thermal model include the loading profiles, the ambient temperature and the top oil temperature (for validation only). However, the excel files provided were enriched with other information (such as several smart metre data, sensor data and weather parameters) which are not useful for estimation purposes. Thus as a first step it was mandatory to pre-process the raw data and write a script to obtain data which is required and discard all other.

The model was and verified using a set of default parameter values for transformer and sample load profiles from the British standard, hard coded into the Python code. These models were then extended for multiple transformers and how the iterative process would work for the fleet on transformers (with necessary screenshots for demonstration).

A web interface was developed to asks users to upload datasets and run the developed model in the back end and show the output (top oil temperature, ageing rate and hot spot) to the web app. The application was provided as a docker-compose project, which wraps a web app developed using the Flask framework in the python programming language. Frontend components are developed with HTML, CSS, and Javascript, with server side rendering using Jinja-2 templating. The project repository is currently hosted at https://github.com/bimec/PLATOON, and access permissions were provided for SAMPOL to fork this repository to its own GitHub or BitBucket account. In the alternative, at SAMPOL's request, a zip file export of the repository including source code and executable release files for Mac and Windows environments will be provided for direct download by SAMPOL at project conclusion. The application may be installed on a user's personal computer, or deployed to a cloud computing instance.

Finally, the models were validated. The validation part is carried out for the transformer (ID transformer_ZIV0004480000). Initially, the model has been executed using the default parameters from the British Standard BS IEC 60076-7 (except for those which are known such as the kVA rating and load to loss ratio).

The figure below shows the calculated top oil temperature plotted and compared against the actual measured values obtained from Sampol, shown in. The two graphs are aligned in their shapes and also the estimated curve is capturing variations. The calculated values for R2, RMSE and MAE are listed in the table below. The R2 is lower than the target and also the RMSE/MAE are slightly away from the set thresholds.

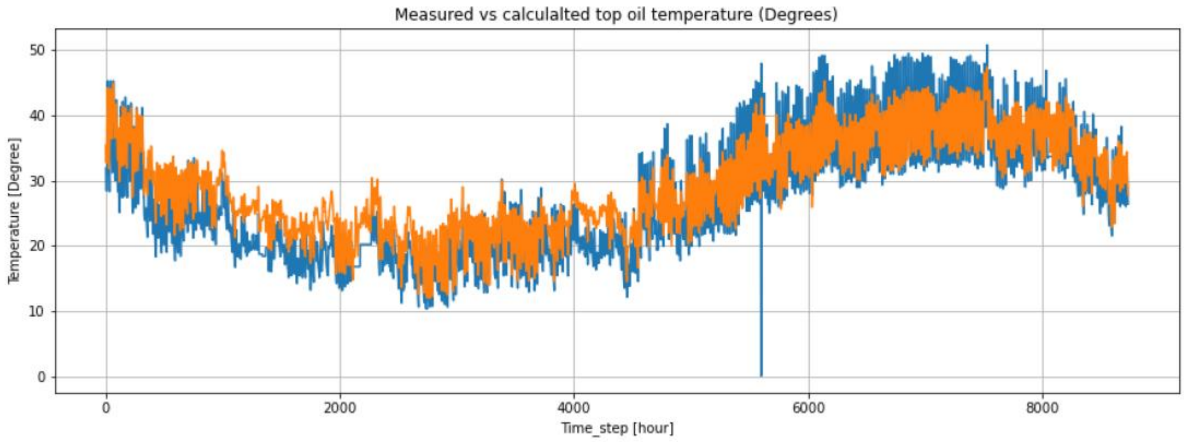


Figure 52: The top oil temperature with default values for parameters. Blue curve: Actual. Orange: Predicted.

Table 10: Target and actual error metrics values for the digital twin thermal model

Performance indices (TPKI) →	R2 (TKPI 4.3)	RMSE (TKPI 4.4)	MAE (TKPI 4.4)
Defined threshold (target values)	>0.95	<5°C	<5°C
Model with default parameters	0.856	5.884°C	5.034°C
Model with tuned parameters	0.9105	3.656°C	3.0°C

3.13.3 Conclusions

The project integrated the IEC60076 thermal into a digital twin that was able to successfully predict the oil temperature for the pilot location transformers. The technical KPIs of RMSE and MAE of less than 5oC were achieved. R^2 error of more than 0.95 was nearly achieved at 0.91 but due to the unusually low loadings of the transformer the model was less accurate.

Future work will use building-level smart-meter data and machine learning techniques to predict the load on 90% of unmonitored transformers. This allows the power networks to actively optimise capacity and flexibility management. Projected savings by Power Utilities anticipate 0.5-1% of their annual network reinforcement budget extrapolating to EU-wide savings of €600million/year for the consumer. Future work will develop digital twin software tools for Power Utilities. The tool will improve decision-making for long-term strategic investment by means of a step-change in building-level electricity demand forecasting. The service will reduce the error associated with transformer load monitoring, reducing the cost of planned infrastructure incurred by Power Utilities and Energy Suppliers. The service will be globally tunable to geographic regions in the EU and US via the CityGML 3.0 standard linking building stock datasets and demographic models. The service will monitor risk from accelerated transformer loss of life and controlled overloading of transformers during peak demand. These two customer groups need to know the electricity demand of buildings but are underserved by existing solutions. Globally there are 205 Power Utilities and 300 Energy Suppliers that require better building-level electricity demand forecasting services. Average customer revenues for digital solution providers are €1.5 million per customer leading to a bottom-up Serviceable Obtainable Market of €350 million. CAGR for digital applications in the energy sector are 27% (Market Monitor 2020) supporting a highly investable market.

4 Discussion and conclusion

In general, all open calls both from first and second rounds were successfully accomplished due to the work conducted by the beneficiaries and the support provided by the technical mentors. Some minor deviations/issues were encountered due to the following aspects:

- Lack of data;
- Integration with PLATOON IDS ecosystem and semantic data models;
- Server Permissions issues;
- Difficulty to share information for confidential deliverables.

However, the above-mentioned deviations/issues were solved via efficient risk management. As a result, the followings lessons were learnt:

- Continuous communication between mentors and beneficiaries, as well as between mentors and the Mentoring Committee was crucial. In this sense an interim MS4 meeting was organised in the 2nd Open Call due to the extensive length of this milestone.
- It was crucial for mentors to engage with pilot leaders and technical partners.
- It was effective to include open call beneficiaries in the technical workshops (e.g. IDS workshops).