Green mobility data models and services for smart ecosystems

D3.1 Green Mobility Services Definition

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Table of Contents

List of Tables

List of Figures

List of Acronyms

Abbreviation / acronym	Description
AEMT	Agencia Estatal de Meteorología
AI	Artificial Intelligence
AQC	Air Quality Calculation
AQF	Air Quality Forecasting Service
AQIC	Air Quality Index Calculation Service
BAF	Bikes Availability Forecasting Service
CO	Carbon Monoxide
CSV	Comma Separated Values
Dx.y	Deliverable number y belonging to WP x
EC	European Commission
EEA	European Environment Agency
LAeq	average sound level measured
LAeq2	average sound level measured during 2h
LAmax	maximum sound level measured
LAmax2	maximum sound level measured in 2h
miMASK	percentage of time that noise exceeds a given threshold 65dB
NAC	Noise Annoyance Calculation Service
NAF	Noise Annoyance Forecasting Service
NGSI-LD	Next Generation Service Interfaces- Linked Data
NO	Nitric Oxide
NO_2	Nitrogen Dioxide

NOX	Nitrogen Oxides
O3	Ozone
PM	Particulate Matter
SO_2	Sulfur Dioxide
SDM	Smart Data Model
TEIC	Traffic Forecasting Impact Calculation Service
TF	Traffic Forecasting Service
TR	Traffic Recommendation Service
kNN	K-Nearest-Neighbor
MSRE	Mean Square Relative Error

Executive Summary

Deliverable "D3.1 Green Mobility services" is the initial and fundamental output of Activity 3 "Green Mobility Services".

This deliverable represents the results of task "T3.1 Green mobility services definition" and paves the way to task "T3.2 Green mobility services development". The main objective of the document is the definition of a set of valued green services. These services were selected by the cities involved in the use cases. The document includes the definition of each selected service and provides a clear plan for their implementation. This means that service diagram, data sources, operativeness, implementation planning, deployment and KPIs for each service are explained in detail.

The cities of Nice, Murcia and Flanders are defined as use cases to identify and test potential applications. So, first step was to gather data from those cities and proposed services that were useful to them. In this sense, services can be classified in: Air Quality, Transport Environmental Impact, Bikes Availability and Noise Annoyance.

The main users of the services are people from the cities (government, citizens, etc.), then it is important to provide them with valuable insights. Therefore, the information provided by the services must be practical and easy to read. To address this, two different kinds of services are proposed: calculation services and forecasting services. The first will output the information that is practical and easy to read. On the other hand, forecasting services will provide the prediction required for calculation services to work.

To illustrate this, Air Quality services consists of two services: Air Quality Calculation (It labels the air quality given some pollutants as good or bad) and Air Quality Forecasting (It predicts the level of pollutants required for the last service, given place and time). This structure is applied for Traffic Services and Noise Annoyance Services too. Calculation in Bikes Availability Service is not required since the output is arranged for use. Additionally, the Traffic Recommendations Service is defined. It feeds from the rest of forecasting services to provide traffic recommendations given place and time.

The relationships between of Activity 3 "Green Mobility Services" and other activities are as follows. The data model that is used in Activity 3 is defined in Activity 2 "Smart Data Models for green mobility". From Activity 4 "Architecture for Context Broker enhancement in concurrent data intensive scenarios as mobility", this activity takes the infrastructure required for the deployment. Activity 5 "Pilots deployment" defines the pilots and provides historical datasets and it will use the services developed in Activity 3. Activity 1 "Project Coordination" and activity 6 "Impact generation and business development" are about management and impact development respectively.

1 Introduction

One of the biggest concerns of the EC are climate change and environmental degradation, as it is written in the Green Deal Strategy [1]. This plan purpose actions over all the aspects that could affect sustainability of Europe and aims to face it in a serious way. In this context, GreenMov project is presented. It proposes the improvement of green and smart mobility for cities pivoting on three main points: generation of Smart Data Models to handle all data, implementation of high-tech services that address the problems from different points of view and the proposal of an infrastructure to integrate all the components that are required.

This deliverable represents the last step of Task 3.1 "Green Mobility Services Definition". The proposal, design and definition of all services are covered within this document. In order to choose and design the services, we have considered, mainly, two aspects: data and potential applications. In this sense, based on availability and quality of data, it is decided to address mobility issues from three angles: Noise Pollution, Traffic and Air Quality. Additionally, the cities of Murcia (Spain), Nice (France) and Flanders (Belgium) are defined as the use cases.

The idea behind is to use open, real-time and predictive technologies to provide tools that helps the cities in this fight. It should not be forgotten that main stakeholders are not the cities but the final users. Therefore, the information provided by the services must be useful and simple at the same time. The services are classified in two groups in this regard.

- Calculation Services: this type undertakes the calculation of a binary variables given an input. For example, regarding Air Quality Index Calculation, this service will classify the air quality as good or bad given the level of some pollutants.
- Forecasting Services: this type is focused on predicting the information required for previous case. Following the example, Air Quality Forecasting will output the level of the pollutants.

The sequential structure (Forecasting Service + Calculation Service) is applied for Air Quality services, Traffic services and Noise Annoyance services. However, we define two additional services that could add value to the project. The first one will predict the number of available docks for a given bike station (location). The output of this service is the number of free docks, so it is not required to use further steps, that is, calculation services to postprocess it. The other service deals with traffic recommendations and it will get as input the output of the rest of Forecasting Services. Thus, the recommendation is based on future-time Noise, Traffic and Air quality criteria.

Following the angles previously pointed, we can classify the services in four categories: Air Quality, Noise Annoyance, Traffic and Bikes Availability. This classification has given rise to the structure of this document, as it will be commented later on this section. Altogether we get four forecasting services (Air quality forecasting, noise annoyance forecasting, traffic forecasting and bikes availability forecasting), three calculation services (air quality index calculation, noise annoyance calculation and traffic environmental impact calculation) and the traffic recommendation service. All services regarding this project are listed below.

- Air quality forecasting: hourly based pollutants estimation.
- Air quality index calculation: binary classification of air quality based on pollutants estimation.
- Traffic forecasting: traffic flow indicators estimation.

- Traffic environmental impact calculation: binary classification based on traffic flow indicators.
- Traffic recommendation: recommendations regarding traffic environmental impact.
- Bikes availability forecasting: bike docks availability estimation.
- Noise annoyance forecasting: noise pollutants estimation.
- Noise annoyance calculation: binary classification of noise annoyance quality based on noise pollutants estimations.

The relationships between Activity 3 and the rest of tasks of this project are illustrated in Figure 1: Activity relationship. The data model that is used in Activity 3 is defined in Activity 2 "Smart Data Models for green mobility". From activity 4 "Architecture for Context Broker enhancement in concurrent data intensive scenarios as mobility", this activity takes the infrastructure required for the deployment. Activity 5 "Pilots deployment" defines the pilots and provides historical datasets and it will use the services developed in Activity 3. Activity 1 "Project Coordination" and activity 6 "Impact generation and business development" are cross-cutting activities devoted to management and impact development respectively.

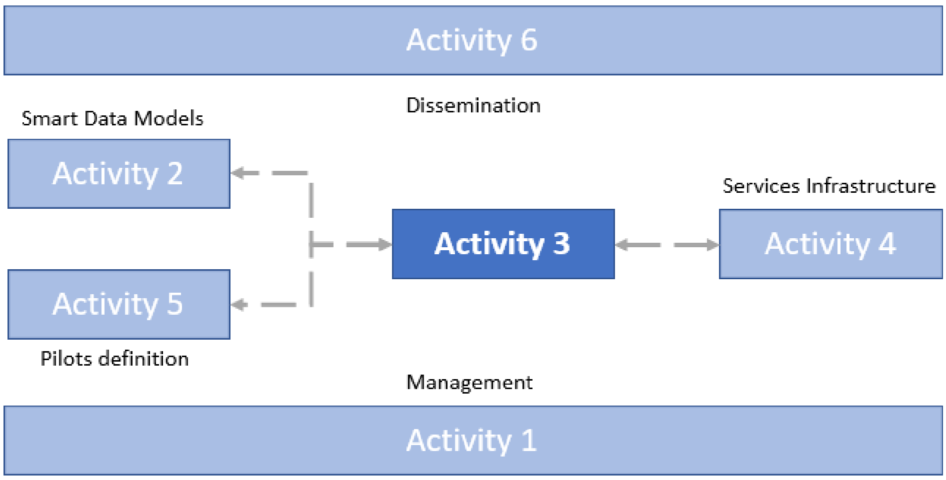

Figure 1: Activity relationship

1.1 Structure of the document

This document is structured in four major sections. For the sake of clarity, we have chosen to use the purpose behind each service for making groups or sections. Thus, we have an Air Quality section, Traffic Environmental Impact section, Bikes Availability section and Noise Annoyance section, besides introduction and conclusion sections.

Chapter 2 presents services regarding air quality.

Chapter 3 presents services regarding traffic environmental impact.

Chapter 4 presents the service regarding bikes availability.

Chapter 5 presents services regarding noise annoyance.

2 Air Quality Services

Services regarding air quality are presented in this section. These services are Air Quality Forecasting and Air Quality Index Calculation.

The AQF service consist of a prediction of certain pollutants levels given a location. The list of pollutants is: Nitric Oxide (NO), Nitrogen Dioxide (NO_2), Particulate Matter with a maximum diameter of 10 microns (PM_{10}), Particulate Matter with a maximum diameter of 2.5 microns ($PM_{2.5}$), Carbon Monoxide (CO), Ozone (O_3) and Sulfur Dioxide (SO_2). Additionally, this service gives an Air Quality Index Forecast, using the AQIF service.

The AQIF service provide a positive number (index) given a set of pollutants.

2.1 Air Quality Forecasting

2.1.1 Description

This service will provide an hourly based estimation of a set of pollutants levels for a given area between two given points in time. Alternatively, if only one point in time is given, it returns an estimation of those pollutants at that time.

2.1.2 Service diagram

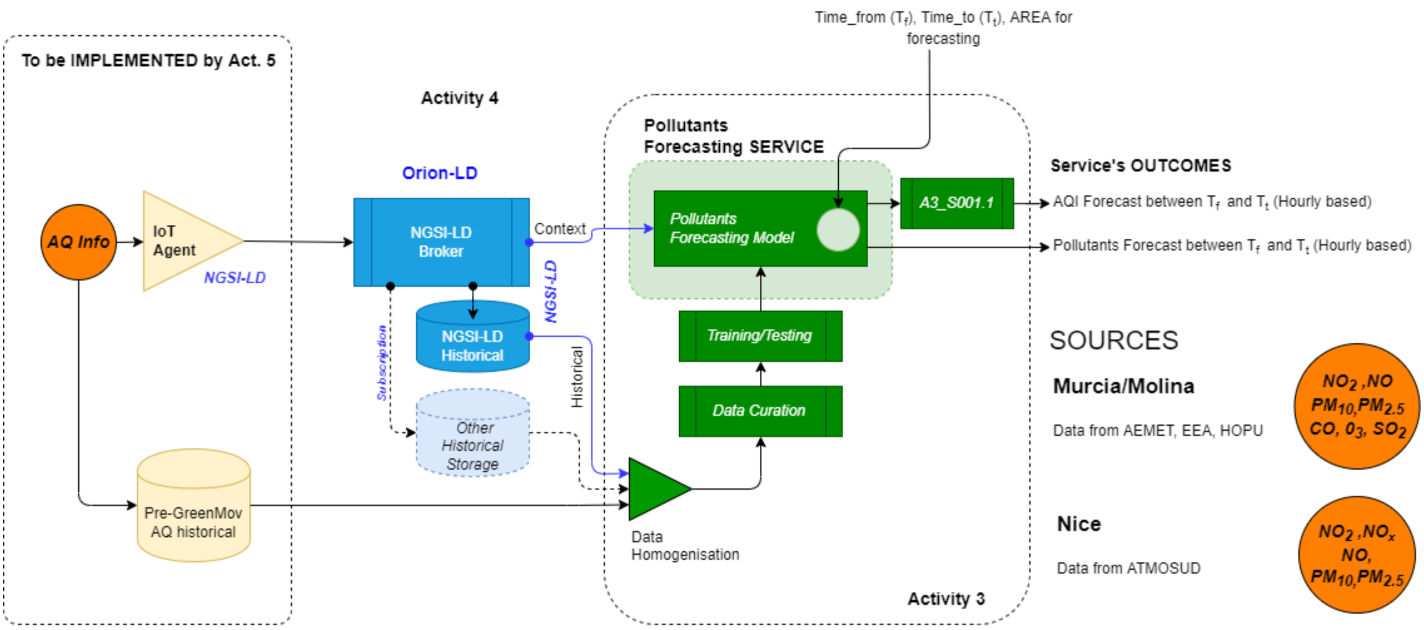

Figure 2. AQF Architecture

2.1.3 Data sources

2.1.3.1 Involved IoT Infrastructure(s)

Murcia/Molina de Segura

Data set involved for the training of the AI model are divided in four groups:

- Data from HOPUs stations.
- Data from Agencia Estatal de Meteorología (AEMET).
- Data from European Environment Agency (EEA).
- Orion LD context broker: For historical and real time (MongoDB) data storage and for the local implementation case.

Nice

The Air Quality Index AQI forecasting service for the use case of Nice will be using different IoT infrastructures for the implementation of the service including:

- Third party cloud services and data bases: for the historical data and for the automation of the real time data extraction.
- NGSI-LD and NGSI-LDES adaptors: To adapt the data format from the third-party cloud services (Nice data platform) to the NGSI-LD and NGSI-LDES format.
- Orion LD context broker: For historical and real time (MongoDB) data storage and for the local implementation case.

2.1.3.2 Smart Data models

The following table presents a list of the smart data models involved in the service where they are described in more detail:

Table 1: SDMs for AQF service

SDM	Link
AirQualityObserved	https://github.com/smart-data-models/dataModel.Environment/tree/92ceb9393f363bf353b10286ca571c8e39b6a455/AirQualityObserved
AirQualityMonitoring	https://github.com/smart-data-models/dataModel.Environment/tree/92ceb9393f363bf353b10286ca571c8e39b6a455/AirQualityMonitoring
WeatherObserved	https://github.com/smart-data-models/dataModel.Weather/tree/7a607dfeaebd3b7164400f46095f86f256062f6b/WeatherObserved
AirQualityForecast	New Data Model

2.1.3.3 Historical Datasets

Murcia/Molina de Segura

Historical data set involved for the training of the AI model are divided in three groups:

- Data from European Environment Agency (EEA): Hourly based information for years from 2013 to 2022 first quarter in two stations located at Murcia. The dataset contains several pollutants measures. The following table summarizes the availability of data:

Table 2: Availability of data for EEA stations

Pollutant	C6H6	NO	NO2	O3	SO2	CO	PM25	PM10
Missing values (%)	33.31	10.10	10.10	9.16	34.58	58.32	91.99	13.055

- Data from Agencia Estatal de Meteorología (AEMET): Daily based information for years from 2013 to 2022 first quarter in two stations located at Murcia. The dataset contains weather information.
- Data from HOPUs stations: Hourly based information for years from 2021 to 2022 first quarter in seven stations located at Molina de Segura. The dataset contains several pollutants measures. The following table summarizes the availability of data.

Table 3. Availability of data for HOPU (Murcia) stations

Pollutant	NO	NO2	O3	SO2	CO	PM25	PM10
Missing values (%)	62.03	53.85	53.93	53.88	53.85	52.92	52.92

Nice:

The historical data sets involved for the training of the AI model and the implementation of the service are:

- Air Quality Index (AQI).
- Nitrogen Dioxide (NO2).
- Nitrogen Monoxide (NO).
- Nitrogen Oxides (NOX).
- PM10 Fine Particles.
- PM2.5 Fine Particles.

Data is extracted from the south of France air quality observatory ATMOSUD for the past 2 years, this data is pre-processed and then fed to a machine learning model.

The historical data is given for years 2013-2021 and the first trimester of 2022.

2.1.3.4 NGSI-LD source

The final service will be fed by NGSI-LD data from the Orion LD context broker of the service as detailed in the service architecture.

2.2 Operativeness

2.2.1.1 Preconditions

Input data is provided in NGSI-LD format.

2.2.1.2 Trigger actions

The trigger action is a request, it is sent to the service to generate a prediction about the air quality index in an area at some specific time in the future, this prediction is used to give an estimate value of the air quality index to the city and the users and will be used as an input for other services deployment.

2.2.1.3 Outcomes

Machine learning models will return a time series of numbers representing the air quality index forecasted in an area for specific time slots in the future.

2.2.1.4 Involved actors

Murcia/Molina de Segura

The involved actors for the development and the operativeness of the service are:

- ATOS.
- HOPU.

Nice:

The involved actors for the development and the operativeness of the service are:

- ATOS.
- ATMOSUD (Observatoire de la qualité de l'air en Région Sud Provence-Alpes-Côte d'Azur).
- IMREDD.
- The City of Nice (Métropole Nice Côte d'Azur).

2.2.1.5 Algorithm data processing

For this service, the approach is to develop regression models to predict discrete timeseries variables.

A statistical model (i.e., Seasonal Holt-Winters [3], Vector ARMA [4], ...) will be used in first place. With a pollutant prediction for each station, a Neural Network will be trained to correct residuals from previous prediction. Then, AQI forecast will be calculated using the Air Quality Index Calculation Service, described in the following section.

The following schema shows the previous explanation for a N stations forecast:

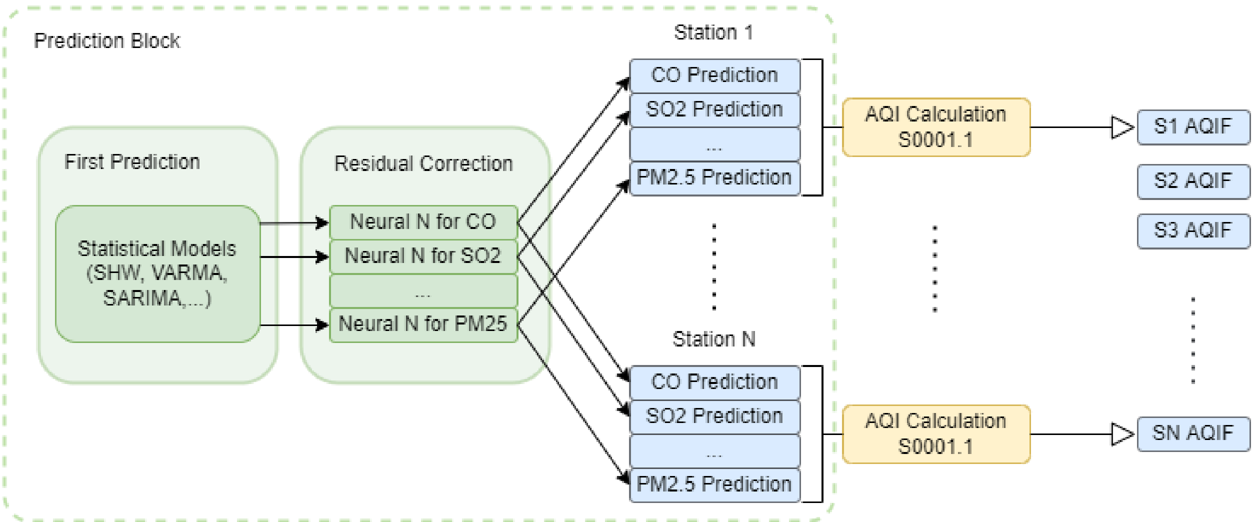

Figure 3. Algorithm schema

2.2.1.6 Success scenario

To measure the success of the developed models, it can be used multiple metrics that compare observed values with predicted values. Most common metrics for forecasting problems are the MAPE, Forecast Error, Mean Absolute Error and Mean Squared Error.

2.2.2 Implementation planning

The first step to start developing the forecasting service is the analysis of historical datasets and its pre-processing.

Once the data is ready to feed different machine learning models, the second step consists in a benchmarking using different algorithms and models trying to find the best performance. Benchmarking should as well include the complexity of the models (description of predictors, regressor analysis, etc.), as well the amount of data as input. It could include the use of Principal Component Analysis.

When the best model has been chosen, the developers must adapt the data inputs to ingest data from NGSI-LD instead of historical CSV files.

The final steps consist in "dockerization" process, where logic functionalities and installation steps are encapsulated on a Docker image looking for an easy deployment.

2.2.3 Service deployment

Thanks to docker image flexibility, there will be two options to deploy the services. On the one hand, the docker image can be integrated in the city's infrastructure. This option allows the services to be tuned for every use case. On the other hand, the docker image can be deployed in a generic cloud to make it more scalable.

2.2.4 Service KPIs

Table 4. AQF KPIs

Indicator	Description	Computation description	Quantification range	Target
Air quality index Forecast model accuracy	Accuracy of the AQI Forecasting model	Real measured Air Quality Index vs. Forecasted Air Quality Index.	[0-100%] 100 is best	75%

2.3 Air Quality Index Calculation

2.3.1 Description

This service calculates air quality based on level of pollutants explained in 2.1. So, given place and time and the corresponding predictions from the forecasting service, the output can either be labelled as good or bad.

2.3.2 Service diagram

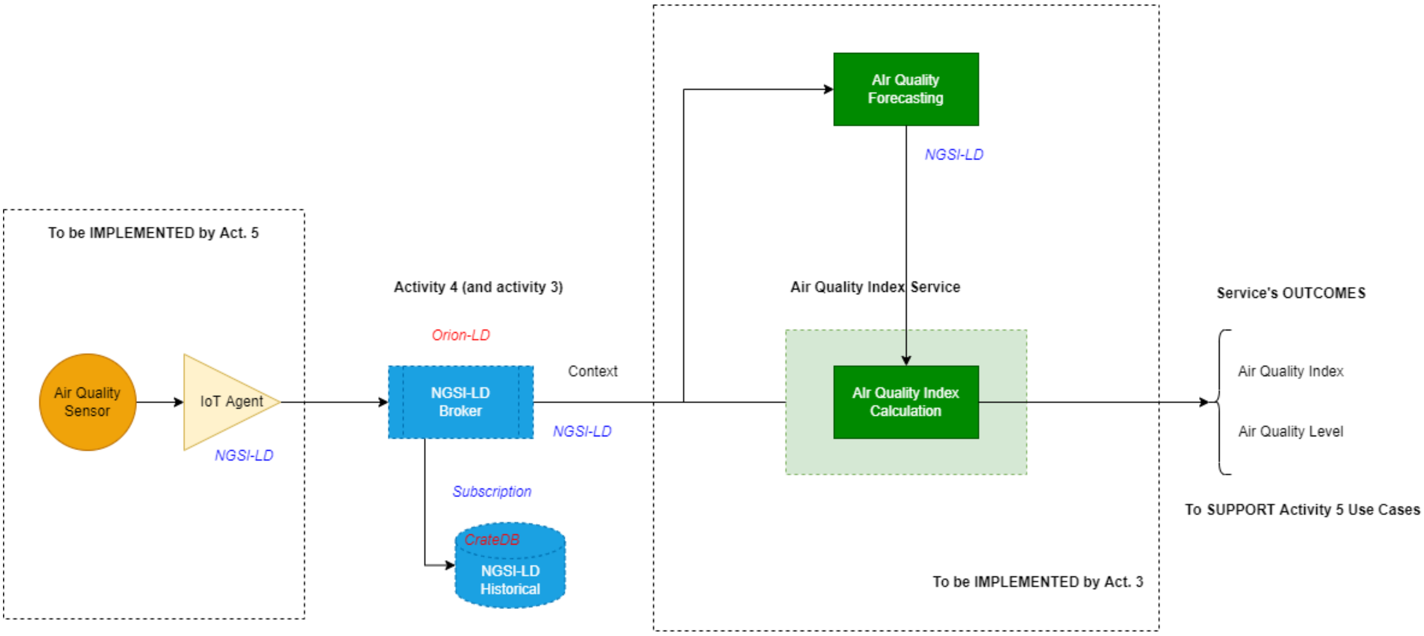

Figure 4. AQIC Architecture

2.3.3 Data sources

2.3.3.1 Involved IoT Infrastructure(s)

Murcia/Molina de Segura

In the Murcia/Molina use case the data needed to make a petition will come from SmartSpot Molina Ciudad Intelligent and European Air Quality Stations in case we want to calculate the Air Quality Index for real time data. On the other hand, if we want to predict a future AQI, data will come from Air Quality Forecasting service.

The service will use a Rest API to receive petitions and send the results back.

Niza

In this use case, data will come from Air Quality Sensors if we want to calculate the Air Quality Index for real time data. If we want to predict a future AQI, data will come from the corresponding forecasting service.

The service will use a Rest API to receive petitions and send the results back.

2.3.3.2 Smart Data models

The list of the smart data models involved in the service are:

Table 5: SDMs for AQC service

SDM	Link
AirQualityObserved	https://github.com/smart-data-models/dataModel.Environment/tree/92ceb9393f363bf353b10286ca571c8e39b6a455/AirQualityObserved

SDM	Link
AirQualityMonitoring	https://github.com/smart-data-models/dataModel.Environment/tree/92ceb9393f363bf353b10286ca571c8e39b6a455/AirQualityMonitoring
AirQualityForecast	New Data Model

2.3.3.3 NGSI-LD source

The data fed to the service via the petition will be in NGSI-LD format. The service will also output the result in NGSI-LD format.

2.3.4 Operativeness

2.3.4.1 Preconditions

Input data must be NGSI-LD.

2.3.4.2 Trigger actions

A petition is received with the AirQualityObserved values for the pollutants defined into the European Air Quality Index.

2.3.4.3 Outcomes

The service will return the European Air Quality Index and the Qualitative Air Quality Level.

2.3.4.4 Involved actors

Murcia/Molina de Segura

The involved actors for the development and the operativeness of the service are:

- ATOS.
- HOPU.

Nice:

The involved actors for the development and the operativeness of the service are:

- ATOS.
- ATMOSUD (Observatoire de la qualité de l’air en Région Sud Provence-Alpes-Côte d’Azur).
- IMREDD.
- The City of Nice (Métropole Nice Côte d’Azur).

2.3.4.5 Algorithm data processing

We will classify the Air Quality Index in function of tabulated values stablished by the European Legislation. This classification will be done for each pollutant and the Air Quality Index reported will be the highest of them. Finally, this index is mapped with the corresponding Qualitative Air Quality Level.

2.3.4.6 Success scenario

The service will prove its accuracy comparing the Air Quality Index reported by sensors and the reported by the reference Air Quality Station.

2.3.5 Implementation planning

The first step will be to define the inputs and outputs of the service and the NGSI-LD models they will use.

The second step will consist in building the service that uses the tabulated values defined by the European Legislation to determine Air Quality Index.

The final steps consist in "dockerization" process, where logic functionalities and installation steps are encapsulated on a Docker image looking for an easy deployment.

2.3.6 Service deployment

Thanks to docker image flexibility, there will be two options to deploy the services. On the one hand, the docker image can be integrated in the city's infrastructure. This option allows the services to be tuned for every use case. On the other hand, the docker image can be deployed in a generic cloud to make it more scalable.

2.3.7 Service KPIs

Table 6. AQIC KPI for service evaluation

Indicator	Description	Computation description	Quantificatio n range	Target
AQI calculation MSRE	Accuracy of the AQI calculation	Real measured Air Quality Index vs. calculated Air Quality Index: Evaluated using Euclidean norm	Real positive number. Zero is best	0.01

3 Traffic Environmental Impact Services

Services regarding traffic environmental impact are presented in this section. These services are: Traffic Forecasting, Traffic Environmental Impact Calculation and Traffic Recommendations Generation.

The Traffic Forecasting service consist of a prediction of the environmental impact of the traffic flow for a given location. Additionally, this service gives an Environmental Impact, using the Traffic Environmental Impact Calculation service. The Environmental Impact service provide a real number (index) given a traffic flow. Finally, the Traffic Recommendations Generation suggests traffic recommendations at a specific location and time.

3.1 Traffic forecasting

3.1.1 Description

The service will provide a prediction of the environmental impact of the traffic flow for a given location and at a specific time given by T. Setting T equals 0 means the current traffic environmental impact.

3.1.2 Service diagram

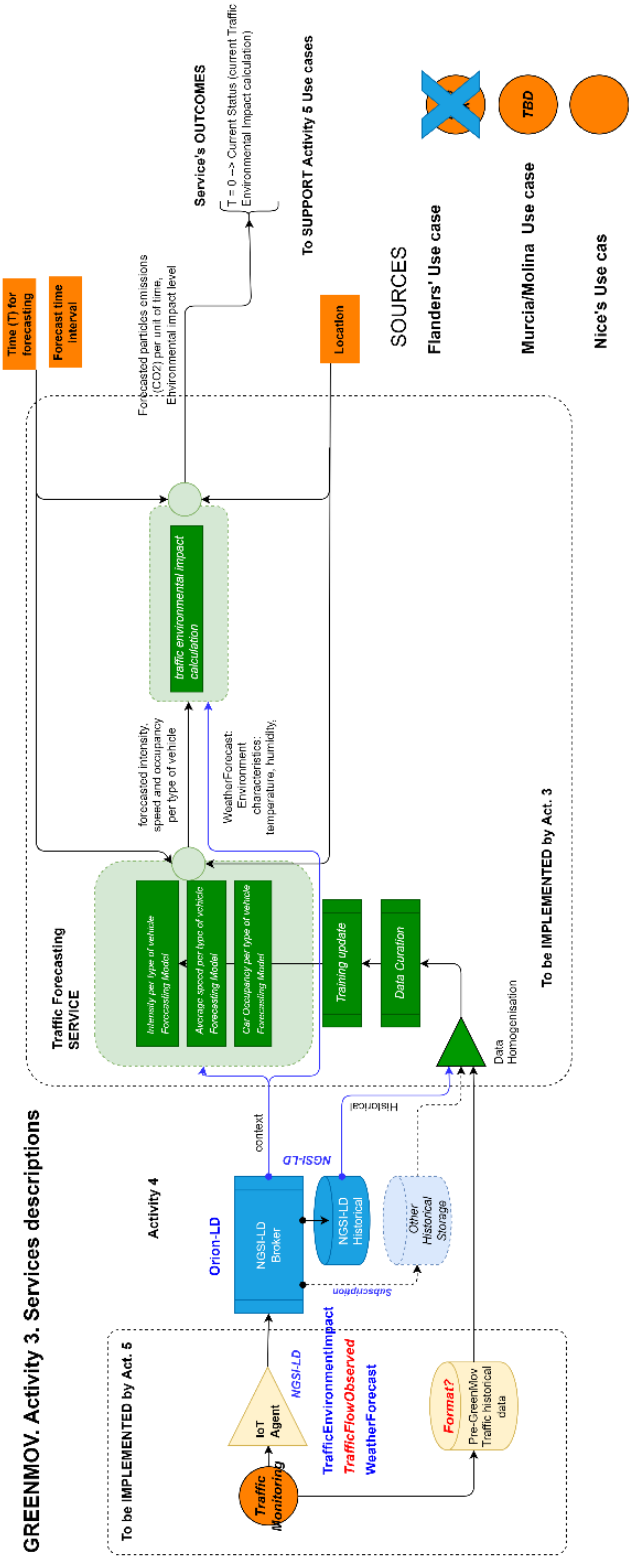

Figure 5. TF Architecture

3.1.3 Data sources

3.1.3.1 Involved IoT Infrastructure(s)

Nice

The Traffic Environmental Impact Forecasting service for the use case of Nice will be using different IoT infrastructures for the implementation of the service including:

- Third-party sensors, cameras, cloud services and data bases: for the historical data and for the automation of the real time data extraction.
- NGSI-LD adaptor: To adapt the data to the NGSI-LD format.
- Orion LD context broker: For historical and real time (MongoDB) data storage and for the local implementation case.

3.1.3.2 Smart Data models

The list of the smart data models involved in the service are:

Table 7: SDMs for TF service

SDM	Link
TrafficEnvironmentImpact	New Data Model
TrafficFlowObserved	https://github.com/smart-data models/dataModel.Transportation/tree/99d905b244c7b7d610a60c3c78f9522e05effc20/TrafficFlowObserved
WeatherForecast	https://github.com/smart-data-models/dataModel.Weather/tree/7a607dfeaebd3b7164400f46095f86f256062f6b/WeatherForecast

3.1.3.3 Historical Datasets

Nice

The historical data sets involved for the training of the AI model and the implementation of the service are:

- Intensity of traffic per type of vehicle;
- Average speed per type of vehicle;
- Car occupancy per type of vehicle;
- Emissions range per type of vehicle;
- Temperature;
- Humidity.

3.1.3.4 NGSI-LD source

Nice

The final service will be fed by NGSI-LD data of the forecasted particles emissions per unit of time and the environmental impact level of the traffic from the Orion LD context broker of the service as detailed in the service architecture.

3.1.4 Operativeness

3.1.4.1 Preconditions

The first precondition for the service deployment is the historical data (Mentioned in Historical Datasets) that is extracted from the third party cloud services, sensors and cameras of the city, in the use case of Nice the data is extracted directly from the city traffic database, the ministry of interior vehicles database along with the AGORA platform for weather, this data is transformed to NGSI-LD format, homogenized, and then pre-processed and fed to a machine learning model for training and testing before the forecasting

3.1.4.2 Trigger actions

The trigger action is a request sent to the service to generate a prediction about the forecasted traffic particles emissions (CO2eq) and the environmental impact level in an area at some specific time in the future, this prediction is used to give an estimate value of the traffic air pollution level to the city and the users and will be used as an input for other services deployment mainly TR service.

3.1.4.3 Outcomes

Machine learning models will return a time series of numbers representing the particles emissions and the environmental impact level in an area for specific time slots in the future.

3.1.4.4 Involved actors

The involved actors for the development and the operativeness of the service are:

- IMREDD;
- French Ministry of Interior;
- The City of Nice (Metropole Nice Côte d'Azur);
- ATOS.

3.1.4.5 Algorithm data processing

For this service, the approach is to develop regression models to predict discrete timeseries variables.

A statistical model (i.e., Seasonal Holt-Winters [3], Vector ARMA [4], ...) will be used in first place. With different traffic parameters prediction in a station, sensor or camera, a Neural Network will be trained to correct residuals from previous prediction. Then, particles emissions forecast will be calculated.

Finally, considering the particles emissions forecast within the area, a rule (such as maximum, average, etc.) will be applied over the values to determine the environmental impact level of the traffic.

3.1.4.6 Success scenario

To measure the success of the developed models, we can use multiple metrics that compare observed values with predicted values. Most common metrics for forecasting problems are: Forecast Error, Mean Absolute Error and Mean Squared Error.

3.1.5 Implementation planning

The first step to start developing the forecasting service is the analysis of historical datasets and its pre-processing.

Once the data is ready to feed different machine learning models, the second step consists in a benchmarking using different algorithms and models trying to find the best performance. Benchmarking should as well include the complexity of the models (number of layers when considering neural network, number of neighbours for kNN, …), but as well the amount of data as input. It could include the use of Principal Component Analysis.

When the best model has been chosen, the developers must adapt the data inputs to ingest data from NGSI-LD instead of historical CSV files.

The final steps consist in "dockerization" process, where logic functionalities and installation steps are encapsulated on a Docker image looking for an easy deployment.

3.1.6 Service deployment

Thanks to docker image flexibility, there will be two options to deploy the services. On the one hand, the docker image can be integrated in city's infrastructure. This option allows the services to be tuned for every use case. On the other hand, the docker image can be deployed in a generic cloud to make it more scalable.

3.1.7 Service KPIs

Table 8. TF KPIs for service evaluation

Indicator	Description	Computation description	Quantificatio n range	Target
% Of the city's traffic addressed	Refers to the percentage of the city's traffic addressed by the implemented solution	Daily traffic measurement in targeted zones vs total traffic in the whole city	[0-100%]	50%

3.2 Traffic environmental impact calculation

3.2.1 Description

The traffic environmental impact services take TF service as an input along with the vehicles plate numbers extracted from traffic cameras of the city and the information attached to them (Type, emissions range ...) to generate the real time or forecasted traffic CO2eq emissions as an outcome.

3.2.2 Service diagram

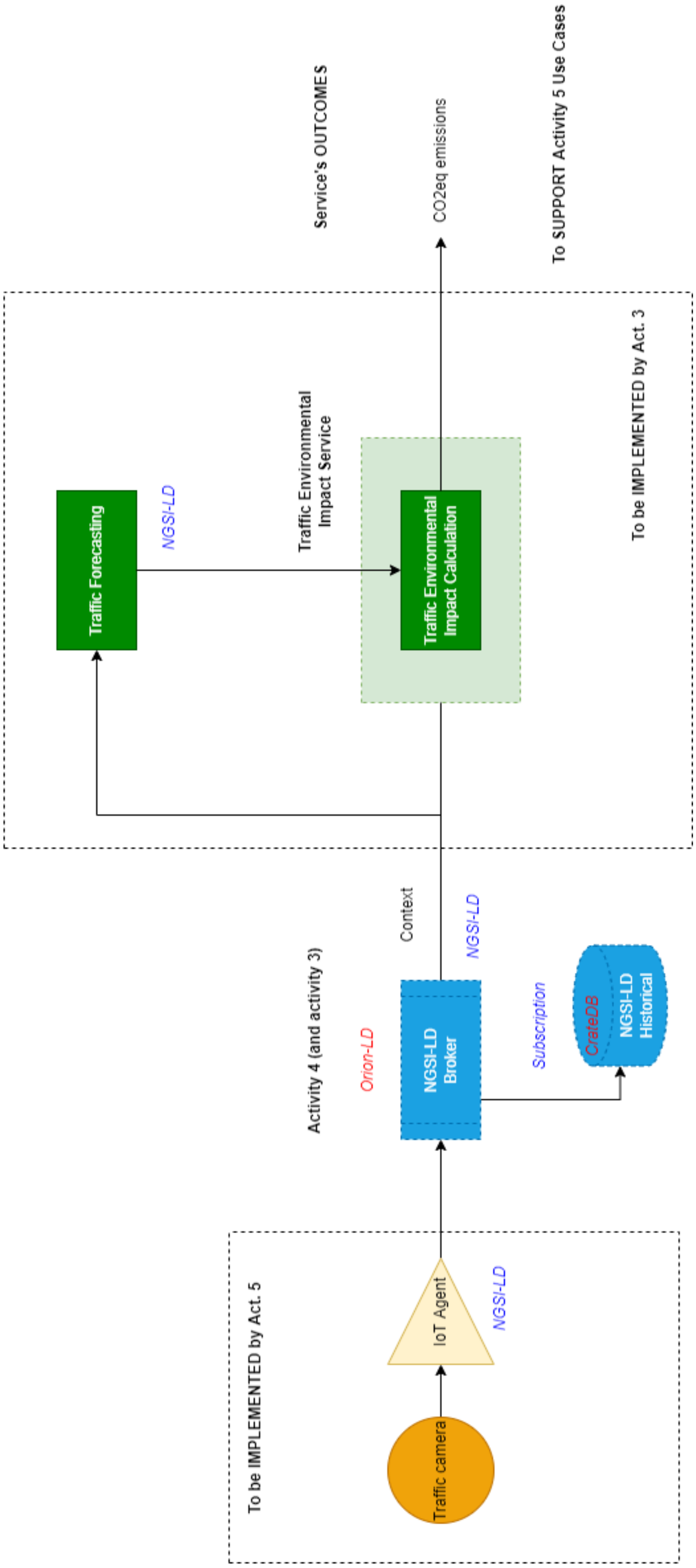

Figure 6. TEIC Architecture

3.2.3 Data sources

3.2.3.1 Involved IoT Infrastructure(s)

Murcia/Molina de Segura

Data required to make a petition will come from Traffic Cameras installed by the city if we want to calculate the Traffic Environmental Impact for real time data, or from the Traffic Environmental Impact Forecast service if we want to predict a future Traffic Environmental Impact.

Nice

Same case as above. Data required to make a petition will come from Traffic Cameras installed by the city in case we want to calculate the Traffic Environmental Impact for real time data, or from the Traffic Environmental Impact Forecast service if we want to predict a future Traffic Environmental Impact.

Both services will use a Rest API to receive petitions and send the results back.

3.2.3.2 Smart Data models

The list of the smart data models involved in the service are:

Table 9: SDMs for TEIC service

SDM	Link
TrafficEnvironmentImpact	New Data Model
TrafficFlowObserved	https://github.com/smart-data models/dataModel.Transportation/tree/99d905b244c7b7d610a60c3c78f9522e05effc20/TrafficFlowObserved
TrafficEnvironmentImpactForecast	New data model

3.2.3.3 NGSI-LD source

The data fed to the service via the petition will be in NGSI-LD format. The service will also output the result in NGSI-LD format.

3.2.4 Operativeness

3.2.4.1 Preconditions

Input data must be NGSI-LD.

3.2.4.2 Trigger actions

A petition is received with the TrafficFlowObserved values needed for the CO2eq emissions calculation.

3.2.4.3 Outcomes

The service will return the CO2eq emissions produced by the input traffic.

3.2.4.4 Involved actors

Murcia/Molina de Segura

The involved actors for the development and the operativeness of the service are:

- ATOS.
- HOPU.
- Ayuntamiento de Murcia.
- Ayuntamiento de Molina.
- Campus de Espinardo.

Nice

The involved actors for the development and the operativeness of the service are:

- IMREDD
- French Ministry of Interior
- The City of Nice (Metropole Nice Côte d'Azur)
- ATOS

3.2.4.5 Algorithm data processing

We will calculate the CO2eq emissions using an indicator for Sustainable Urban Mobility stablished by the European Commission in Mobility and Transport [2].

3.2.4.6 Success scenario

The service will be capable of returning a correct calculation of the CO2eq emissions.

3.2.5 Implementation planning

The first step will be to define the inputs and outputs of the service and the NGSI-LD models they will use.

The second step will consist in building the service that uses the formula defined by the European Commission to determine CO2eq emissions.

The final steps consist in the "dockerization" process, where logic functionalities and installation steps are encapsulated on a Docker image looking for an easy deployment.

3.2.6 Service deployment

Thanks to docker image flexibility, there will be two options to deploy the services. On the one hand, the docker image can be integrated in city's infrastructure. This option allows the services to be tuned for every use case. On the other hand, the docker image can be deployed in a generic cloud to make it more scalable.

3.2.7 Service KPIs

Table 10: TEIC KPIs for service evaluation

Indicator	Description	Computation description	Quantification range	Target
Traffic emissions accuracy	The traffic emissions calculation is coherent with Copernicus	Traffic emissions inventories vs. accumulated traffic emissions calculated by our service: Evaluated using Euclidean norm	[0-100%] 100 is best	80%

3.3 Traffic recommendations

3.3.1 Description

The service will provide traffic recommendations at a specific location and time given by time T. Setting T equals 0 means the current traffic environmental recommendation.

3.3.2 Service diagram

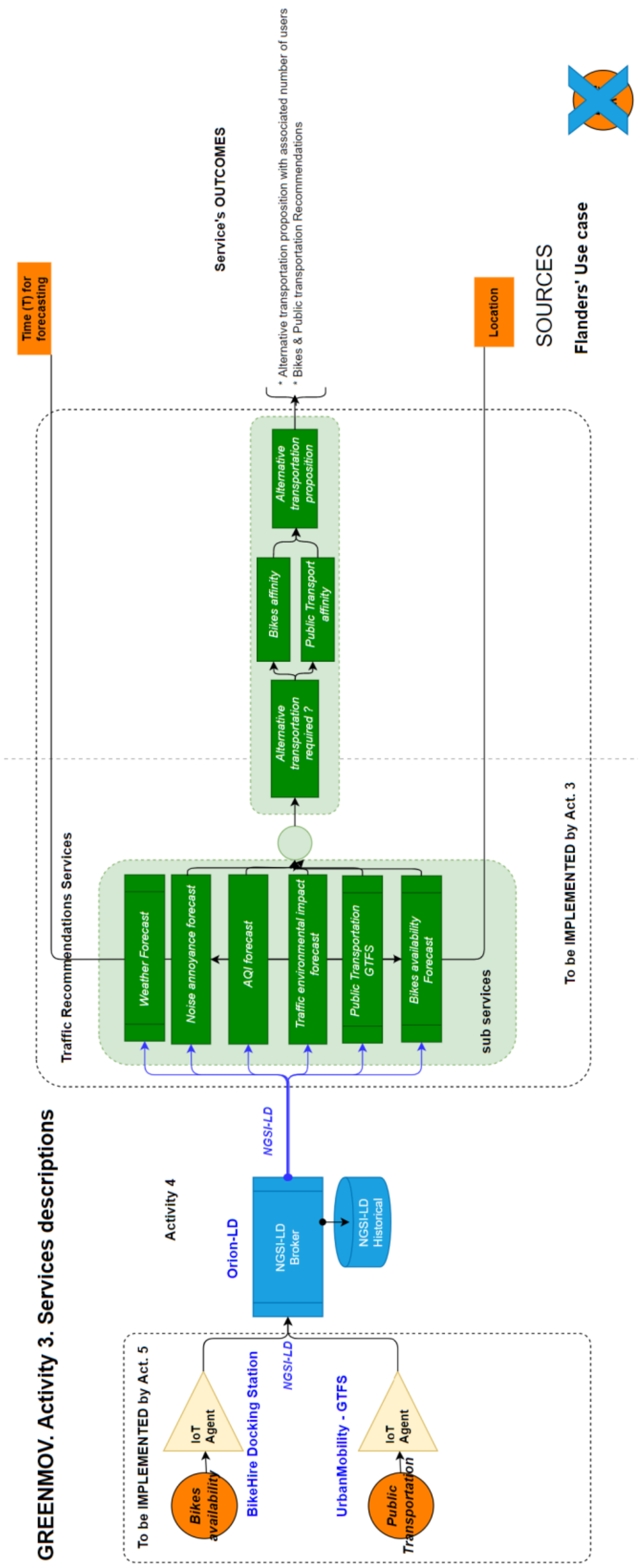

Figure 7. TR Architecture

3.3.3 Data sources

3.3.3.1 Involved IoT Infrastructure(s)

Nice

TR service for the use case of Nice will be using different IoT infrastructures for the implementation of the service including:

- Third party cloud services and data bases: for the historical data and for the automation of the real time data extraction.
- NGSI-LD adaptors: To adapt the data format from the third-party cloud services to the NGSI-LD format.
- Orion LD context broker: For historical and real time data storage and for the local implementation case.

3.3.3.2 Smart Data models

The list of the smart data models involved in the service are:

Table 11: SDMs for TR service

SDM	Link
BikeHireDockingStation	https://github.com/smart-data-models/dataModel.Transportation/tree/99d905b244c7b7d610a60c3c78f9522e05effc20/BikeHireDockingStation
UrbanMobility	https://github.com/smart-data models/dataModel.Transportation/tree/99d905b244c7b7d610a60c3c78f9522e05effc20/TrafficFlowObserved
AirQualityForecast	New data model
NoiseAnnoyanceForecast	New data model
TrafficEnvironmentalImpactForecast	New data model
BikesAvailabilityForecast	New data model

3.3.3.3 NGSI-LD source

Nice

The final service will be fed by NGSI-LD data from the Orion LD context broker of the service as detailed in the service architecture.

3.3.4 Operativeness

3.3.4.1 Preconditions

The first precondition for the service deployment is the GTFS transportation data that is extracted from the third party cloud services of the city, in the use case of Nice the data is extracted from the open data platform of the city of Nice (http://opendata.nicecotedazur.org/data/dataset/export-quotidien-au-format-gtfs-du-reseau-de-transport-lignes-d-azur), this data is pre-processed and then fed to the service model along with other sources of data, mainly the outputs of different forecasting services deployed by the project such as :

- Noise annoyance forecast;
- AQI forecast;
- Traffic environmental impact forecast;
- Bike availability forecast;

3.3.4.2 Trigger actions

The trigger action is a request sent to the service to generate a recommendation about alternative transportations available for the users in an area in real time, this proposition is used to give a greener alternative solution to the users and will be used as an input for other services deployment mainly the Alternative transport availability forecasting.

3.3.4.3 Outcomes

The service model will return a result representing the traffic recommendation in a location for a specific time.

3.3.4.4 Involved actors

Nice

The involved actors for the development and the operativeness of the service are:

- IMREDD;
- The City of Nice (Métropole Nice Côte d'Azur);
- Régie Lignes d'Azur (Trams and buses Operator);
- ZOU (Trains Operator);
- VéloBleu (Bikes operator);
- ATOS;
- ATMOSUD (Observatoire de la qualité de l'air en Région Sud Provence-Alpes-Côte d'Azur);
- The City of Nice noise platform AGORA.

3.3.4.5 Algorithm data processing

For this service, the approach is to develop a model that combines different parameters.

This model will digest other services outputs such as Noise Pollution, Air Quality and Traffic environmental impact but also will take in consideration the public transportation alternatives and bikes available nearby at that time to generate a recommendation for the users based on the previously mentioned parameters.

3.3.4.6 Success scenario

To measure the success of the developed models, first the number of recommendations per day is calculated, the more a survey can be conducted to know the user's feedback about this service and their degree of satisfaction, also the city can be a judge of the success of this service by providing its point of view) on how this service impacted the traffic and the environment before and after the deployment.

3.3.5 Implementation planning

The first step to start developing the service is the analysis of public transportation and the other forecasted datasets that will be used and their pre-processing.

Once the data is ready to feed the model, the second step consists in a benchmarking using different algorithms and models trying to find the best results. Benchmarking should as well include the complexity of the models (type of parameters), but as well the amount of data as input.

The final steps consist of the "dockerization" process, where logic functionalities and installation steps are encapsulated on a Docker image looking for an easy deployment.

3.3.6 Service deployment

Thanks to docker image flexibility, there will be two options to deploy the services. On the one hand, the docker image can be integrated in city's infrastructure. This option allows the services to be tuned for every use case. On the other hand, the docker image can be deployed in a generic cloud to make it more scalable.

3.3.7 Service KPIs

Table 12. TR KPI for service evaluation

Indicator	Description	Computation description	Quantification range	Target
Daily recommendation number	Refers to the number of recommendations provided by the service implemented in the Nice's use case, based on the traffic density and air quality assessment. A recommendation can either be a short-term recommendation to change transportation for public transport, or to not change anything	Number of recommendations per day averaged over two weeks' time of the experimentation	Highest is best	2

4 Bikes Availability Service

The Bikes Availability Forecasting Service consist of a prediction of available docks for a given bikes station and time range. This prediction is useful for the user, so no index calculation is required. The weather of the given bike station will be used as an input for the service.

4.1 Bike s availability forecasting

4.1.1 Description

The Bicycle Availability Forecasting (BAF) service consists of estimating the number of bikes available, given a bike station and a time.

4.1.2 Service diagram

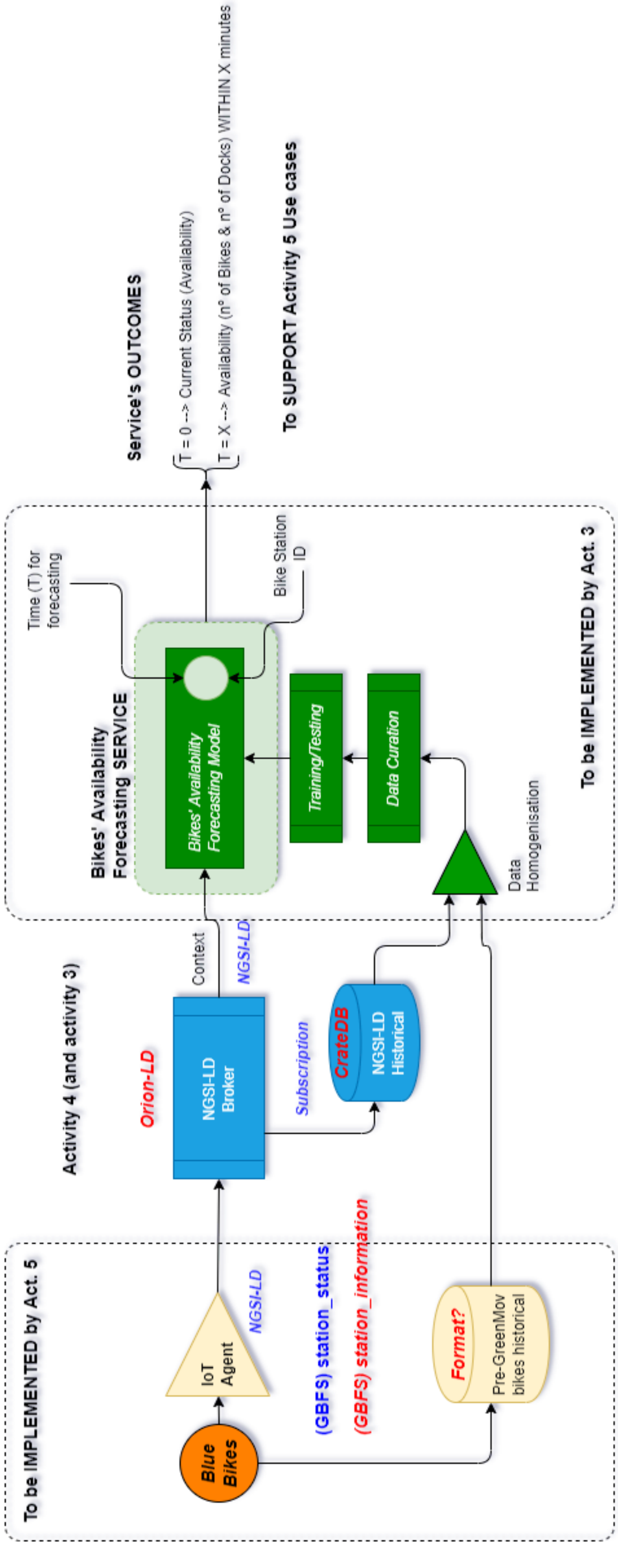

Figure 8. BAF Architecture

4.1.3 Data sources

4.1.3.1 Involved IoT Infrastructure(s)

Flanders

Data set involved for the training of the AI model is provided by:

- Data from Blue Bike.
- Orion LD context broker: For historical and real time (MongoDB) data storage and for the local implementation case.

Nice

Data set involved for the training of the AI model is provided by:

- VéloBleu historical data for 5 stations (www.velobleu.org):
  - TotalCapacity;
  - BikesAvailable.
- Orion LD context broker: For historical and real time (MongoDB) data storage and for the local implementation case.

Murcia/Molina de Segura

Data set involved for the training of the AI model is provided by:

- MuyBici historical data for 2 stations in Espinardo Campus (https://muybici.org/):
  - TotalCapacity;
  - BikesAvailable;
  - BikesOccupied;
  - Municipality;
  - Location;
  - Datetime.
- Orion LD context broker: For historical and real time (MongoDB) data storage and for the local implementation case.

4.1.3.2 Smart Data models

The list of the smart data models involved in the service are:

Table 13: SDM for BAF service

SDM	Link
(OSLO.PassengerTransportHubs) BicycleParkingStationPTH-AP	New Data Model

4.1.3.3 Historical Datasets

Historical data set involved for the training of the AI model consist of a dataset with the following characters:

- *StationName:* name of the bike station;
- *bikesAvailable*: number of bikes available at time indicated in ‘datetime’;
- *docksInUse:* number of free docks at time indicated in ‘datetime’;
- *latitude;*
- *longitude;*
- *station;*
- *datetime;*

4.1.3.4 NGSI-LD source

The final service will be fed by NGSI-LD data from the Orion LD context broker of the service as detailed in the service architecture.

4.1.4 Operativeness

4.1.4.1 Preconditions

Data input must be NGSI-LD and follow SDM format.

4.1.4.2 Trigger actions

The trigger action to generate a prediction about the number or the percentage of bikes and docks that are available in some specific bike station at some specific time slot is the request that any user can generate using a mobile device or a computer.

Ideally, this request will be generated some minutes before the desired time slot to predict.

4.1.4.3 Outcomes

Machine learning models will return the number or the percentage of bikes and docks that are available in the requested station. Other relevant outcome are the different metrics that developers use to measure the success of each model.

4.1.4.4 Involved actors

For the process of development of this service, there are two main actors. The first one is the dataset that contains specific data from each bike station. The second actor is the model which returns the better results after performing the benchmarking.

Other external actors are the users that will use the service, making a request, to obtain the number of bicycles and docks that are available in any bike station.

4.1.4.5 Algorithm data processing

For this service, the strategy aims to develop and test different forecasting models. This approach is similar to developing regression models to predict continuous variables, but, taking into account that all past data compose a time series. The algorithm used is based on a Population Continuous Time Markov Chain model.

The forecasting problem can be solved using linear and nonlinear algorithms from Scikit-Learn library, developing deep learning models with TensorFlow or using predefined models like Prophet model by Facebook, among other options.

4.1.4.6 Success scenario

To measure the success of the developed models, it can be used multiple metrics that compare observed values with predicted values. Most common metrics used in forecasting problems are: Forecast Error, Mean Absolute Error and Mean Squared Error.

4.1.5 Implementation planning

The first step to start developing the forecasting service is the analysis of historical datasets and its pre-processing.

Once the data is ready to feed different machine learning models, the second step consists in a benchmarking using different algorithms and models trying to find the best performance Benchmarking should as well include the complexity of the models (description of predictors, regressor analysis, etc.).

When the best model has been chosen, the developers have to adapt the data inputs to ingest data from NGSI-LD instead of historical CSV files.

The final steps consist in the “dockerization” process, where logic functionalities and installation steps are encapsulated on a Docker image looking for an easy deployment.

4.1.6 Service deployment

Thanks to docker image flexibility, there will be two options to deploy the services. On the one hand, the docker image can be integrated in city’s infrastructure. This option allows the services to be tuned for every use case. On the other hand, the docker image can be deployed in a generic cloud to make it more scalable.

4.1.7 Service KPIs

Table 14: BAF KPI for service evaluation

Indicator	Description	Computation description	Quantification range	Target
Bikes availability MSRE	Residual error of prediction	Real bikes availability vs predicted bikes availability using Euclidean norm	Real positive number. Zero is best	1.5

5 Noise Annoyance Services

In this section, monitoring services for noise pollution are presented. Following the structure of other services explained in this document, it consists in two steps. First, different magnitudes are forecasted. These magnitudes are LAeq (average sound level measured each 15min), LAmax (maximum sound level measured), LAeq2 (average sound level measured during 2h), LAmax2 (maximum sound level measured in 2h), noiseOrigin (source of the recorded noise at installation of the sensor) and miMASK (percentage of time that noise exceeds a given threshold 65dB). The forecast will be obtained by service 5.1. Noise annoyance forecasting

Once the output of the last step is collected, service 5.2 Noise Annoyance calculation will be responsible of applying threshold rules in order to get a label. One hour period is defined for the prediction. So, the output will consist of one prediction per hour within given time range provided by the user.

5.1 Noise annoyance forecasting

5.1.1 Description

The service will provide the noise annoyance level for a given location and within T minutes. Setting T equals 0 means the current noise annoyance forecasting.

5.1.2 Service diagram

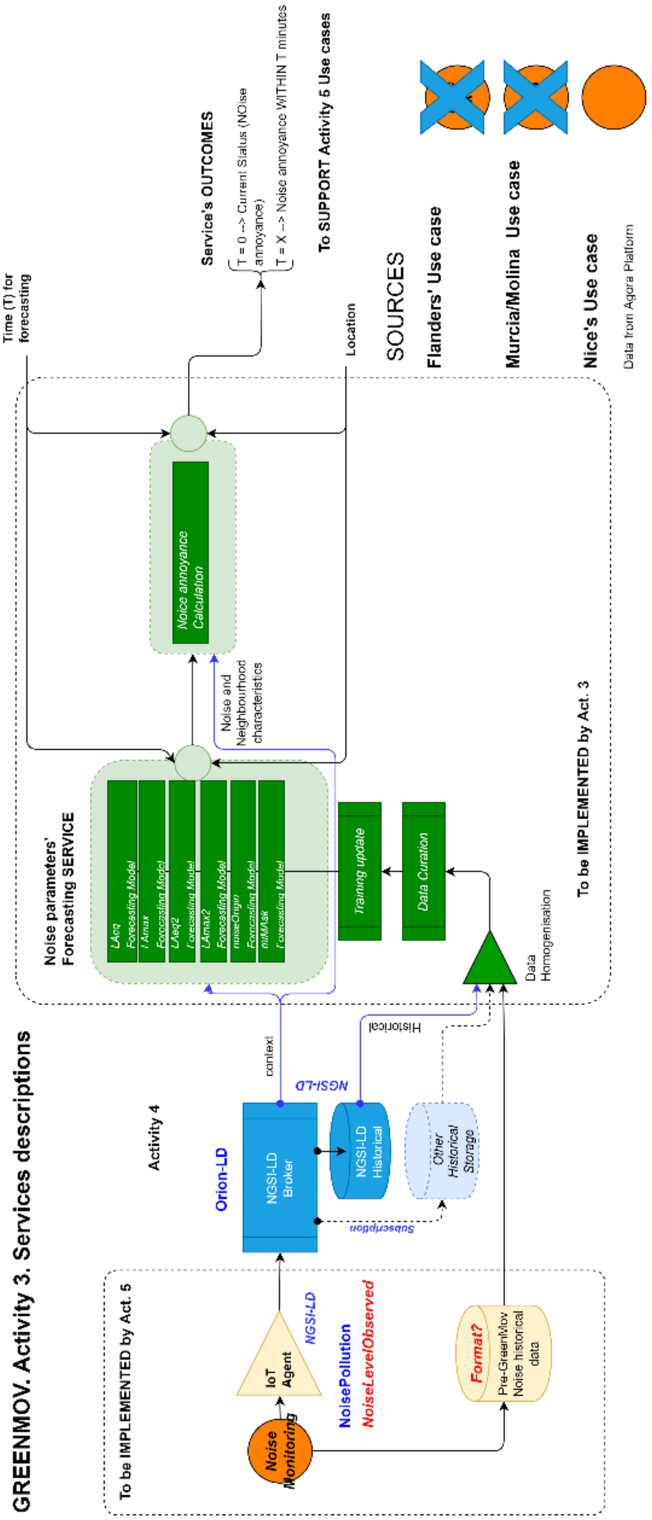

Figure 9. NAF Architecture

5.1.3 Data sources

5.1.3.1 Involved IoT Infrastructure(s)

Nice

The NAF service for the use case of Nice will be using different IoT infrastructures for the implementation of the service including:

- Third-party cloud services and data bases: for the historical data and for the automation of the real time data extraction.
- NGSI-LD adaptor: To adapt the data format from the third-party cloud services (Agora platform) to the NGSI-LD format.
- Orion LD context broker: For historical and real time (MongoDB) data storage and for the local implementation case.

5.1.3.2 Smart Data models

The list of the smart data models involved in the service are:

Table 15: SDM for NAF service

SDM	Link
NoisePollution	New Data Model
NoiseLevelObserved	https://github.com/smart-data-models/dataModel.Environment/tree/92ceb9393f363bf353b10286ca571c8e39b6a455/NoiseLevelObserved

5.1.3.3 Historical Datasets

Nice

The historical data sets involved for the training of the AI model and the implementation of the service are:

- LAeq (Average sound level measured each 15min);
- LAmax (Maximum sound level measured);
- LAeq2 (Average sound level measured during 2h);
- LAmax2 (Maximum sound level measured in 2h);
- noiseOrigin (Main origin (source) of the recorded noise at installation of the sensor);
- miMASK (Percentage of time that noise exceeds a given threshold 65dB).

5.1.3.4 NGSI-LD source

Nice

The final service will be fed by NGSI-LD data from the Orion LD context broker of the service as detailed in the service architecture.

5.1.4 Operativeness

5.1.4.1 Preconditions

The first precondition for the service deployment is the historical data (Mentioned in Historical Datasets) that is extracted from the Third-party cloud services of the city, in the use case of Nice the data is extracted from the city noise monitoring platform AGORA along with the calculated noise annoyance, this data is transformed to NGSI-LD format, homogenized, and then pre-processed and fed to a machine learning model for training and testing before the forecasting.

5.1.4.2 Trigger actions

The trigger action is a request sent to the service to generate a prediction about the noise annoyance level in an area at some specific time in the future, this prediction is used to give an estimate value of the noise annoyance level to the city and the users and will be used as an input for other services deployment

5.1.4.3 Outcomes

Machine learning models will return a time series of numbers representing the forecasted noise annoyance level in an area for specific time slots in the future.

5.1.4.4 Involved actors

The involved actors for the development and the operativeness of the service are:

- IMREDD;
- The City of Nice (Metropole Nice Côte d'Azur);
- ATOS.

5.1.4.5 Algorithm data processing

For this service, the approach is to develop regression models to predict discrete timeseries variables.

A statistical model (i.e., Seasonal Holt-Winters [3], Vector ARMA [4], ...) will be used in first place. With different noise parameters prediction in a station, a Neural Network will be trained to correct residuals from previous prediction. Then, noise annoyance forecast will be calculated.

Finally, considering the station noise annoyance forecast within the area, a rule (such as maximum, average, etc.) will be applied over the values.

Based on resources, the number of Neural Network models might change.

5.1.4.6 Success scenario

To measure the success of the developed models, it can be used multiple metrics that compare observed values with predicted values. Most common metrics for forecasting problems are: Forecast Error, Mean Absolute Error and Mean Squared Error.

5.1.5 Implementation planning

The first step to start developing the forecasting service is the analysis of historical datasets and its pre-processing.

Once the data is ready to feed different machine learning models, the second step consists in a benchmarking using different algorithms and models trying to find the best performance. Benchmarking should as well include the complexity of the models (number of layers when considering neural network, number of neighbours for kNN, …), but as well the number of data as input. It could include the use of Principal Component Analysis.

When the best model has been chosen, the developers have to adapt the data inputs to ingest data from NGSI-LD instead of historical CSV files.

The final steps is the "dockerization" process, where logic functionalities and installation steps are encapsulated on a Docker image looking for an easy deployment.

5.1.6 Service deployment

Thanks to docker image flexibility, there will be two options to deploy the services. On the one hand, the docker image can be integrated in city's infrastructure. This option allows the services to be tuned for every use case. On the other hand, the docker image can be deployed in a generic cloud to make it more scalable.

5.1.7 Service KPIs

Table 16. NAF KPI

Indicator	Description	Computation description	Quantification range	Target
Noise annoyance forecast model accuracy	Accuracy of the noise annoyance forecasting model	Real noise vs. Forecasted noise: Evaluated using Euclidean norm	[0-100%] 100 is best)	Noise annoyance forecast model accuracy

5.2 Noise Annoyance calculation

5.2.1 Description

The service will provide the noise annoyance calculation for a given location and within T minutes. Setting T equals 0 means the current noise annoyance calculation.

5.2.2 Service diagram

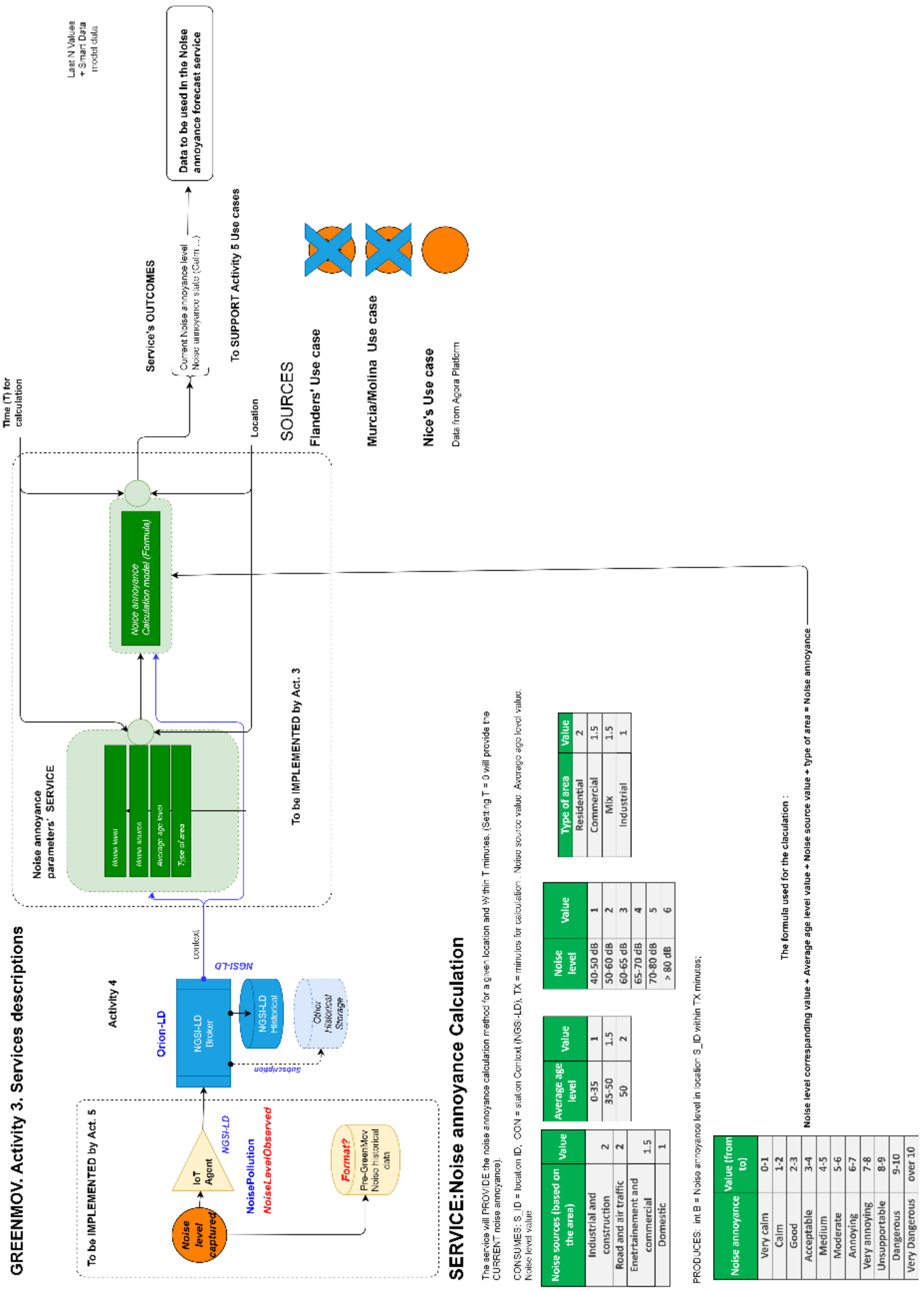

Figure 10. NAC Architecture

5.2.3 Data sources

5.2.3.1 Involved IoT Infrastructure(s)

Nice

NAC service for the use case of Nice will be using different IoT infrastructures for the implementation of the service including:

- Third party cloud services and data bases: for the historical data and for the automation of the real time data extraction.
- NGSI-LD adaptor: To adapt the data format from the third-party cloud services (Agora platform) to the NGSI-LD format.
- Orion LD context broker: For historical and real time (MongoDB) data storage and for the local implementation case.

5.2.3.2 Smart Data models

The list of the smart data models involved in the service are:

Table 17: SDM for NAC service

SDM	Link
NoisePollution	New Data Model
NoiseLevelObserved	https://github.com/smart-data-models/dataModel.Environment/tree/92ceb9393f363bf353b10286ca571c8e39b6a455/NoiseLevelObserved

5.2.3.3 NGSI-LD source

Nice

The final service will be fed by NGSI-LD data from the Orion LD context broker of the service as detailed in the service architecture.

5.2.4 Operativeness

5.2.4.1 Preconditions

The first precondition for the service deployment is the historical data (Mentioned in Historical Datasets) that is extracted from the third-party cloud services of the city. In the use case of Nice, the data is extracted from the city noise monitoring platform AGORA with other data from the INSEE (The French National Institute of Statistics and Economic Studies), this data is transformed to NGSI-LD format, homogenized, and then pre-processed and used to calculate the noise annoyance level.

5.2.4.2 Trigger actions

The trigger action is a request sent to the service to generate a calculation of the noise annoyance level in an area in real time (or historical) taking in consideration different parameters, this calculation is used to give an estimate value of the noise annoyance level to the city and the users and will be used as an input for other services deployment such as noise annoyance forecasting.

5.2.4.3 Outcomes

The calculation models will return a time series of numbers representing the noise annoyance level in an area for specific time slots (Real-time or historical).

5.2.4.4 Involved actors

The involved actors for the development and the operativeness of the service are:

- IMREDD;
- The City of Nice (Metropole Nice Côte d'Azur):
- ATOS.

5.2.4.5 Algorithm data processing

For this service, a mathematical formula is used to calculate the noise annoyance level, this indicator helps determine the disturbance caused by noise in a specific area and taking in consideration the noise level and other multiple parameters such as the noise source, the age level of the population in the area and the type of the area.

5.2.4.6 Success scenario

To measure the success of the developed indicator, it can be used multiple methods that compare a citizen's sample perception values with calculated values. Most common method is to conduct an on-site survey and compare it to the actual value of the service.

5.2.4.7 Implementation planning

The first step to start developing the service is the analysis of historical datasets and its pre-processing.

Once the data is ready to feed the calculation models, it is transformed to the NGSI-LD format and transferred to the Orion LD Broker before being used in the calculation model

5.2.5 Service deployment

Thanks to docker image flexibility, there will be two options to deploy the services. On the one hand, the docker image can be integrated in city's infrastructure. This option allows the services to be tuned for every use case. On the other hand, the docker image can be deployed in a generic cloud to make it more scalable.

5.2.6 Service KPIs

The SERVICE KPIs that tracks the proper development and deployment of the service:

Table 18: NAC KPI

Indicator	Description	Computation description	Quantification range	Target
Noise annoyance calculation accuracy	Accuracy of the noise annoyance calculation model	Real noise annoyance perceived vs. calculated noise annoyance: Evaluated using on-site survey	[0-100%] 100 is best	75%

6 Conclusions

This document is the report regarding task 3.1, Green Mobility Service Definition. During the task, the cities and technical partners have been analysing data coming from use cases in order to detect cities needs and propose solutions to solve these needs. Findings extracted in this regard are:

- The main stakeholders of the applications are people from the cities. This means that the applications should provide useful and easy-to-read information. In this sense, services are divided into:
  - Forecasting services: intermediate predictions.
  - Calculation services: final output based on these intermediate predictions.
- The services focus on the development of predictive tools that allows people and cities come ahead of time. The approach is based on three fundamental aspects:
  - Air Quality;
  - Traffic environmental impact;
  - Noise Annoyance.

In light of the above, all the services are defined and explained within this document. The aspects that are covered, to be more specific, are architecture schema, data sources, operativeness, implementation planning, key performance indicators and service deployment. Thus, all the steps during development life are raised.

The inputs to this deliverable from the rest of activities are as follows:

- Activity 2 “Smart Data Models for green mobility”: definition of SMD used across services.
- Activity 4 “Architecture for Context Broker enhancement in concurrent data intensive scenarios as mobility”: definition of infrastructure to deploy services on production environment.
- Activity 5 “Pilots deployment”: provide historical datasets in SMD format.

Future work will consist of sticking to guidelines presented in this document, which corresponds to planning activities of Task 3.2 “Green Mobility Services Development”. This report can be seen as the result of Task 3.1. Green Mobility Services Definition” activities will continue into Task 3.2 “Green Mobility Services Development” and the outcomes will be compiled in the corresponding deliverable 3.2. “Green mobility services v2”.

7 References

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