



PHYSICS

OPTIMIZED HYBRID SPACE-TIME SERVICE CONTINUUM IN FAAS

D6.6 – PHYSICS APPLICATION PROTOTYPE V2

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¹ Lead Beneficiary, Contributor, Internal Reviewer, Quality Assurance

² Can be left void

LIST OF ABBREVIATIONS

Term	Explanation
BPMN	Business Process Model and Notation
CLA	Command Line Argument
CSP	Cloud Service Provider
CYBE	CybeleTech
D	Deliverable
DEM	Demonstrator
DFKI	Deutsches Forschungszentrum für Künstliche Intelligenz [German Research Centre for Artificial Intelligence]
ETL	Extract, Transform, Load
FaaS	Function as a Service
GPU	Graphics Processing Unit
HTTP	HyperText Transfer Protocol
iSPRINT	Innovation Sprint
JSON	JavaScript Object Notation
NRT	Near-Real-Time
OW	OpenWhisk
QC	Quality Control
RAMP	Reusable Artefacts Marketplace Platform
RIA	Research and Innovation Action
SaaS	Software as a Service
T	Task
WP	Work Package

EXECUTIVE SUMMARY

The goal of this deliverable, which is of type *Demonstrator*, is to accompany the three demonstrators built for the three pilots: Smart Manufacturing, eHealth, and Smart Agriculture and document the internal prototype milestone of the project.

These use-cases cover three very distinct application scenarios (i.e., manufacturing, health, and agriculture) that cover three major areas of European everyday life and economic activity. We thus demonstrate the benefits of the PHYSICS platform in a broad range of application scenarios and show how to improve agility and adoption by applying more advanced computing models and cover a wide and diverse range of available edge resources (e.g., small IoT sensors, mobile devices, or Edge nodes in diverse clusters).

The current document D6.6: PHYSICS Application Prototype V2 is the final of a series of 2 deliverables that mark the “Version 1” and “Version 2” releases of these prototypes and are being produced in the context of Task T6.3: Use Cases Adaptation and Experimentation.

In this document you will find, the following elements:

- A brief overview of the PHYSICS Project and the PHYSICS Platform – to provide the necessary context for the remainder of the document we describe the high level aims of the PHYSICS project, as well as the high-level PHYSICS technical architecture, consisting of Infrastructure Layer, Continuum Deployment Layer, and Application Developer Layer – the last of which allows the development of the three prototypes as described in this document.
- An overview and short description of design decisions that were made in the process of producing the demonstrators for the three use cases. For all three use cases we provide a short summary of their aims and objectives and highlight the major Functional Requirements that have been fulfilled.
- Descriptions of the three demonstrators produced, covering the use cases of Smart Manufacturing, eHealth, and Smart Agriculture. For each use case, it is described how Node-RED flows are designed and used to implement the application flow, and how the use cases are deployed in the PHYSICS Platform. For each use case, the fulfillment of functional requirements is detailed, leading to the final versions of the services for evaluation.

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1 INTRODUCTION

This document, D6.6: PHYSICS Application Prototype V2, accompanies the final version of three separate demonstrators that are delivered under this Task 6.3 Use Cases Adaptation & Experimentation. As the name of the task implies, the activities in this slice of the PHYSICS project deal with adapting the Use Cases (*Smart Manufacturing*, *eHealth*, and *Smart Agriculture*) to the PHYSICS Platform-to-be in an experimental fashion. The three use cases mentioned have in some detail been defined in T6.2: Use Case Scenarios, as described in D6.4: PHYSICS Application Scenarios Definition V2 (Franke, et al., 2022). For the current document to be understandable in isolation, we provide a short summary of each of the use cases in the relevant subsection of Section 3, but we refer to the details regarding requirements for each of the Use Cases to the D6.4 document. We also built this document on top of its predecessor, D6.5: PHYSICS Application Prototype V1 (op den Akker, et al., 2022), resulting in a single document containing all relevant information on experimentation.

Although requirements have been captured in a very systematic way, this Use Case “Adaptation & Experimentation” is indeed a more experimental process. Due to the dynamic nature of the PHYSICS platform in the early stages of the project’s development, in which new features and functionalities are implemented continuously. Nevertheless, and again to maintain a document that is self-contained, we aim to provide a quick overview of the PHYSICS platform and architecture in Section 2 of this document.

The core contents of this deliverable describe the final version of the application demonstrators as developed by the three use case partners. This is described in Section 4 of this document.

1.1 Objectives of the Deliverable

The objective of this deliverable is to demonstrate three use case prototypes, in the Smart Manufacturing, eHealth, and Smart Agriculture domains respectively, and how they use the PHYSICS Platform and platform components. This document is part of the deliverable, accompanying those prototypes and serving as a guide for the preparation and experimentation leading to their delivery for evaluation.

1.2 Insights from other Tasks and Deliverables

Figure 1 shows the timeline of activities for Task 6.3 under which this document is delivered. As shown, this document builds on the previously delivered documents D2.5: PHYSICS Reference Architecture Specification V2 (Patiño, et al., 2022) – describing the reference architecture of PHYSICS and D6.2: Prototype of the Integrated PHYSICS solution framework and RAMP V2 (Mamelli, et al., 2023) – describing a recent state of the integrated PHYSICS platform, as well as D6.4: Application scenarios definition V2 (Franke, et al., 2022) - describing the definitions and requirements for the use cases.

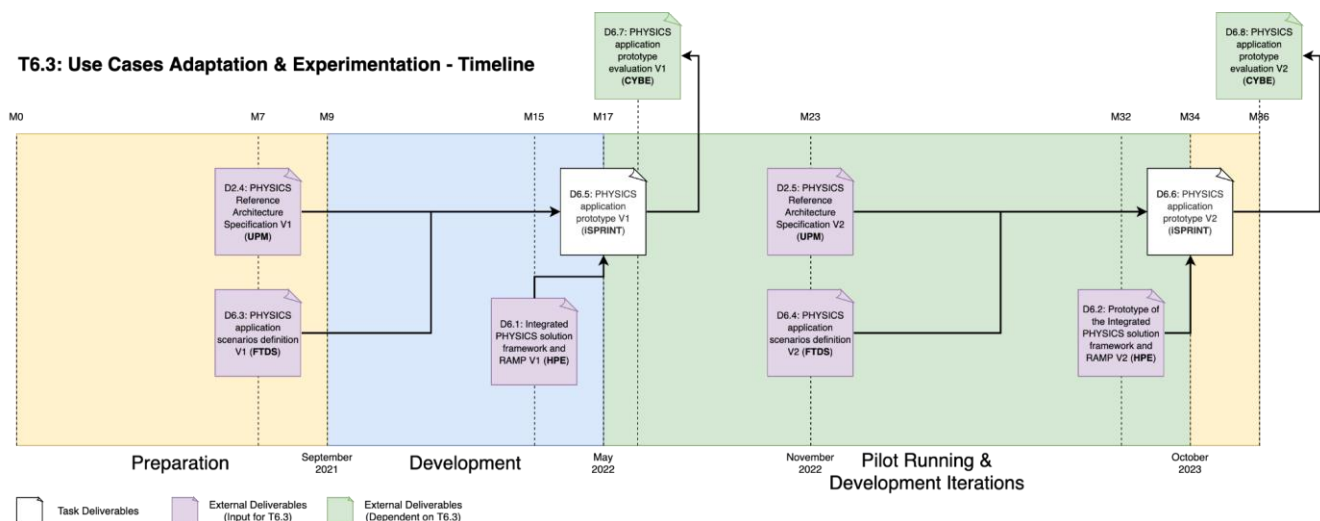


Figure 1: Timeline for T6.3 including dependencies between the various relevant deliverables.

1.3 Structure

The remainder of this document is structured as follows. Section 2 gives a brief overview of the PHYSICS architecture. This overview is not meant to be exhaustive, but merely provides some context to better understand the contents of the following sections. Section 3 provides a short overview as well as any potentially relevant design specifications of the three different use cases: Smart Manufacturing, eHealth and Smart Agriculture. In Section 4, the actual prototype demonstrators for the use cases are described, and finally conclusions and an outlook for future work is provided in Section 5.

1.4 Changes since D6.5

The changes in this document compared to the previous version (op den Akker, et al., 2022) are grouped per use case. For the smart manufacturing, the changes are as follows:

- Minor changes in section 3.1.
- Input & Output JSON specifications updated in section 4.1.1.
- Updated existing flow to final version in section 4.1.1.
- Added newly implemented flow in section 4.1.2.
- Updated function requirement fulfillment section 4.1.3.

For the eHealth use case, the main area of update is the optimization and finalization of the inference scenario, as well as the introduction of two more scenarios on phenotyping and synthesis. In detail the following sections have been updated as explained:

- Introduced patient phenotyping and data synthesis cases alongside inferencing as goals of the use case in section 3.2.1.
- Updated the specifications of the use case in section 3.2.2.
- Updated sections 4.2.1 and 4.2.2, to include the flows on phenotyping and synthesis. Also updated the figures therein to reflect the latest version of the design environment.
- Completely re-written section 4.2.4, to reflect the final experimentation results.

Finally, for the smart agriculture use case the main area of update is the introduction of two more pipelines. The changes are as follows:

- Minor updates in section 4.3.1 (introduction of subsections for conformity)
- Implementation, deployment and testing of simulation pipeline as a service in a new section 4.3.2.
- Implementation, deployment and testing of calibration pipeline as a service in a new section 4.3.3.
- Parallelization of the calibration pipeline taking advantage of FaaS in section 4.3.3.

There are also horizontal changes across the use cases, that are as follows:

- The introduction section 1 is updated.
- This section (1.4) is new.
- The references have been updated throughout the document.
- The concluding section 5 is re-written.

2 OVERVIEW OF PHYSICS ARCHITECTURE

The PHYSICS platform architecture is described in D2.5: PHYSICS Reference Architecture Specification V2 (Patiño, et al., 2022). In the rest of this section we provide a short summary of the overall objectives for the PHYSICS project and platform (section 2.1), as well as the platform architecture (section 2.2), in order to help better understand the prototypes as described in Section 4.

2.1 The PHYSICS Project

PHYSICS empowers European Cloud Service Providers (CSPs) to exploit the most modern, scalable and cost-effective cloud model, operated across multiple service and hardware types, provider locations, edge, and multi-cloud resources. To this end, it applies a unified continuum approach, including functional and operational management across sites and service stacks, performance through the relativity of space (location of execution) and time (of execution), enhanced by semantics of application components and services. PHYSICS applies this scope via a vertical solution consisting of:

- A *Cloud Design Environment*, enabling design of visual workflows for applications, exploiting provided generalized Cloud design patterns functionalities with existing application components, easily integrated and used with FaaS platforms, including incorporation of application-level control logic and adaptation to the FaaS model.
- An *Optimized Platform Level FaaS Service*, enabling CSPs to acquire a cross-site FaaS platform middleware including multiconstraint deployment optimization, runtime orchestration and reconfiguration capabilities, optimizing FaaS application placement and execution as well as state handling within functions, while cooperating with provider-local policies.
- A *Backend Optimization Toolkit*, enabling CSPs to enhance their baseline resources performance, tackling issues such as cold-start problems, multi-tenant interference and data locality through automated and multi-purpose techniques.

Furthermore, PHYSICS will produce an Artefacts Marketplace (RAMP) (see (Mamelli, et al., 2023)), in which internal and external entities (developers, researchers, etc.) will be able to contribute fine-grained reusable artifacts (such as functions, flows, or controllers). PHYSICS will validate the outcomes in 3 real-world applications (eHealth, Agriculture and Manufacturing), making a business, societal and environmental impact on the lives of EU citizens.

2.2 Basic Architecture

The following summary of the PHYSICS Architecture has been adopted from (Mamelli, et al., 2023). The main components of the PHYSICS architecture are shown in Figure 2. There three layers are depicted from top to bottom: (1) the *Application Developer Layer*, (2) the *Continuum Deployment Layer* and (3) the *Infrastructure Layer*, which correspond to the developments in the three technical work packages of the PHYSICS project:

- WP3: Functional and Semantic Continuum Services Design Framework (Application Layer)
- WP4: Cloud Platform Services for Global Space-Time Continuum Interplay (Continuum Deployment Layer)
- WP5: Extended Infrastructure Services with Adaptable Algorithms (Infrastructure Layer)

The top layer, Application Developer Layer, is the entry point for users that design their applications using a Visual Workflow tool. The design of applications is eased by reusing common design patterns such as split-join for function parallelization, batch processing, data collection, and more, provided by the Design Patterns Repository. Application components (e.g., functions) can be semantically annotated providing information to lower layers that may affect the placement, deployment, operation and configuration of the application (Semantic Models). Application components may have elasticity controllers that regulate the algorithms and resources needed for scaling a component.

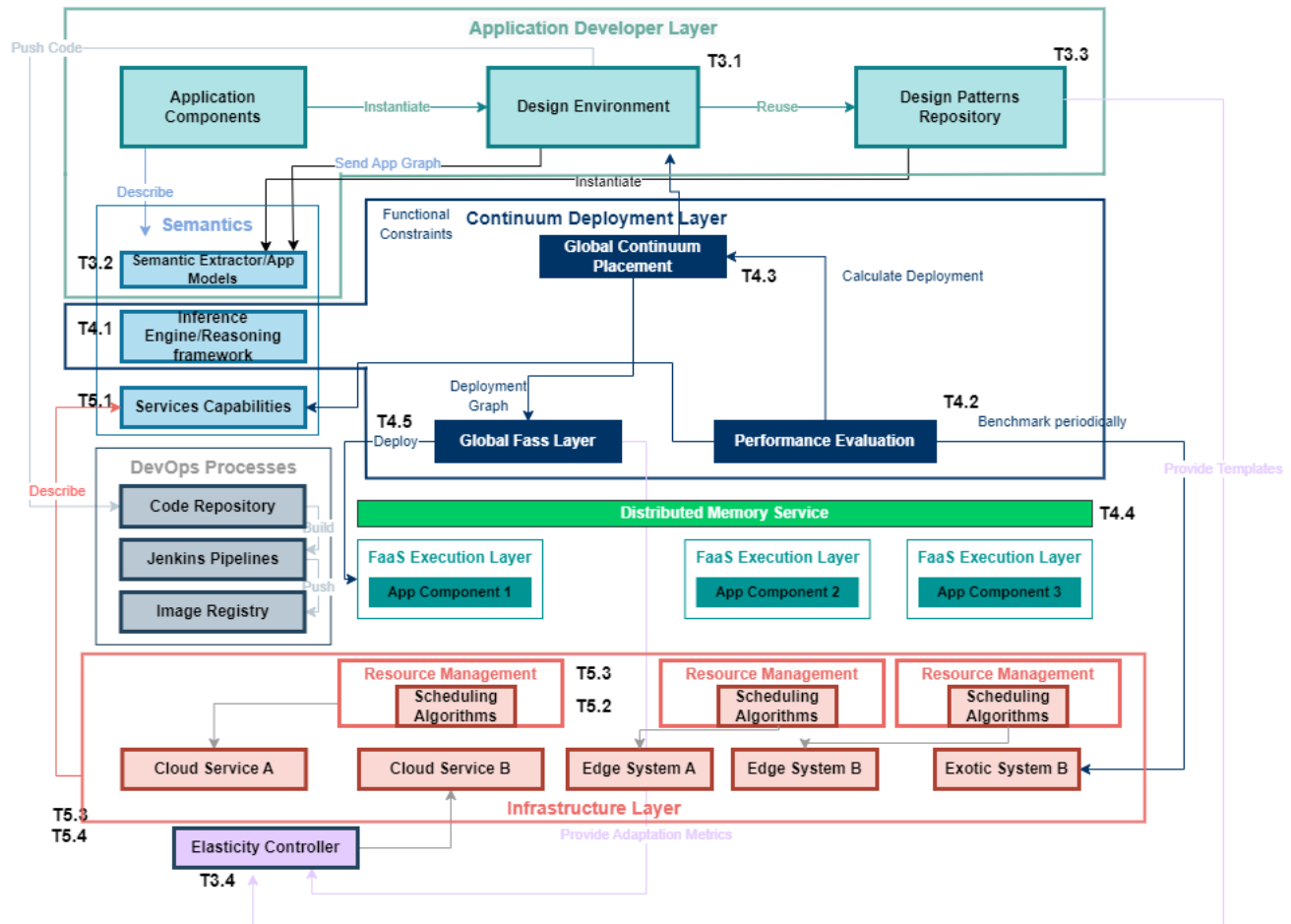


Figure 2: The PHYSICS Software Components' Architecture.

The Continuum Deployment Layer oversees providing uniform access to the diverse cloud services provided by one or more cloud providers. The Global Continuum Placement oversees deciding on the most suitable deployment of applications taking into account the performance of the services, costs and affinity constraints of components. For that purpose, it receives the list of candidate services that the Reasoning Framework has filtered taking into account the application graph needs and the performance of the services provided by the cloud services and edge devices Performance Evaluation component. The placement of the components is done by the Global FaaS Layer component. The Global FaaS Layer abstracts the usage of different data centers from one or more cloud providers. The management of data shared by functions of applications is provided at this level by the Distributed Memory Service.

The Infrastructure Layer provides a view and interface for enabling an optimized operation of the edge and cloud services utilized for the realization of the application service graph. To this end, the Service Capabilities component depicts and models the abilities of each service and resource type. The analysis of different algorithmic approaches for adaptive and real-time provider level scheduling (Scheduling algorithms) so that resources are adapted to current application needs while maintaining overall QoS levels is done by the Resource Management component. The co-allocation strategies component provides, on behalf of the provider strategies, optimizations to maximize performance.

3 USE CASES: OVERVIEW AND DESIGN

As explained in the introduction section of this deliverable document, the main contents of the document are split into two parts. This section provides short overviews of the three different use cases and gives room to document any design decisions or functional specifications that were used to create the actual prototypes that are described in Section 4.

In the following three sub-sections, we provide for each of the three use cases, a short summary or synopsis to refresh the reader on the context of the use case, as well as any design or specifications that may be of interest or required to understand certain development choices that were made in the development of the prototypes. Note that each of the use cases define their own design and functional specifications, based on the use-case specific requirements that were finalized earlier in D6.4 (Franke, et al., 2022).

3.1 Use Case: “Smart Manufacturing”

3.1.1 Synopsis

SmartFactory-KL provides an Industry 4.0-compliant and manufacturer-independent demonstrator for the PHYSICS-Project. The integration of SmartFactory-KL with the PHYSICS platform enables the decoupling of the available services in the production line. The initial version of the pilot plant already follows a service-oriented approach, which made it easier to convert it into a Function-as-a-Service (FaaS) system. Within the Smart Manufacturing use case, two scenarios were defined. One of the scenarios implements a failover case. In case of the local Quality Control (QC) service failure, the system is expected to forward the QC request to the PHYSICS-Platform and continue the QC without downtime. The second use case develops a more complex QC service following FaaS approach, which is expected to increase the certainty level³, in case the local QC service fails to provide an adequate value. Initially, the local QC service utilizing PHYSICS at the edge with low computing resources will be used for a faster analysis. If the certainty level is not satisfactory, then the system will forward the QC data to the complex QC service and perform computations with more available resources.

An important factor in both use cases is the priority of the Local and Cloud version of the services. In both, the local services have precedence. If the local QC service does not function properly or not at all, then the QC service in the Cloud will be used. The PHYSICS-Platform (which will be used at the edge and Cloud) and FaaS approach enable higher availability which was not available at the initial version of the pilot plant.

3.1.2 Design & Specifications

As stated above, for the Smart Manufacturing pilot, two scenarios were defined. The first prototype implemented only the second scenario since it had minimum dependency with the development progress of the PHYSICS components. Now that all required PHYSICS components are available, both smart manufacturing scenarios are implemented.

The “to-be” BPMN diagrams for the scenario have been defined in Deliverable 6.3 (Franke, et al., 2022). For easier trackability, the diagram of the second scenario is also given in Figure 3.

To realize the Smart Manufacturing use cases, the functional requirements shown in the Table 1 are defined.

³ Or “score” of AI-based results.

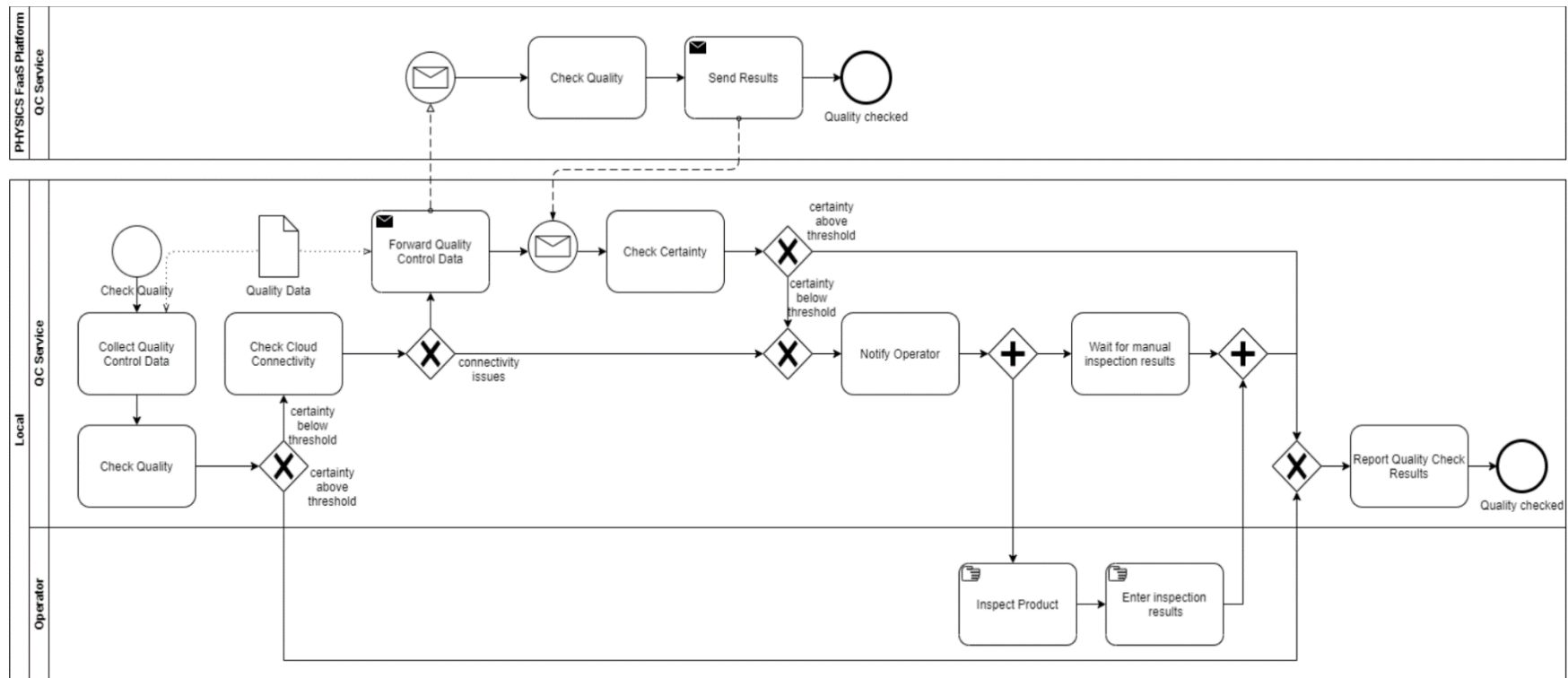


Figure 3: BPMN Diagram of Scenario #2 of the Smart Manufacturing Pilot.

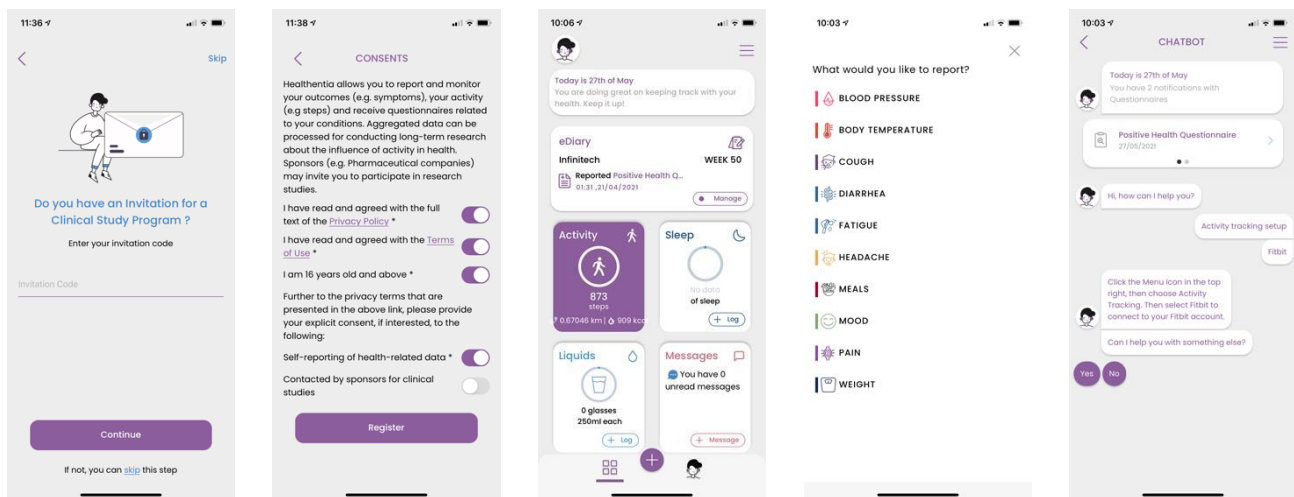
Table 1: Functional Requirements of the Smart Manufacturing Use Case.

Code	Functional Requirements
FRS-UC1-01	An inference service for quality control must be provided to be invoked by DFKI.
FRS-UC1-02	The inference service is to be deployed according to the principles of the PHYSICS project through the OpenWhisk platform.
FRS-UC1-03	The inference service is to be utilized via the endpoints exposed by Node-RED flows.
FRS-UC1-04	The inference will take place in a custom docker-based OpenWhisk action.
FRS-UC1-05	The inference service is to be invoked by specifying the inputs (image and other quality related data) to infer upon and the model to be used.
FRS-UC1-06	The inference service tolerates the server failures by utilizing the PHYSICS platform (Edge & Cloud).
FRS-UC1-07	The inference service runs preferably on the local Edge.

3.2 Use Case: “eHealth”

3.2.1 Synopsis

The aim of the “eHealth” Pilot is to improve the performance and maintainability of the Healthentia platform, developed by Innovation Sprint (iSPRINT), by using Function-as-a-Service (FaaS) technologies as provided by the PHYSICS Platform for some of the smart services on offer. Healthentia is an eClinical Software-as-a-Service (SaaS) platform, consisting of a mobile app for patients/citizens, a web portal for healthcare professionals and researchers, and a server-platform for data storage and processing (see Figure 4 for an impression of the mobile app and its functionalities – as taken from (Franke, et al., 2022)).

**Figure 4: Screenshots of the Healthentia mobile application.**

Deliverable 6.3 (Franke, et al., 2022) provides all details and requirements for this Use Case. In order to better understand the provided functional specifications and prototype description (see section 4) we include a summary of a typical usage scenario here:

An individual interested in monitoring or improving their health or lifestyle will download the Healthentia mobile application to their phone. The user provides an email address and password and finalizes their account creation by consenting to their data being used for research purposes. Once in the application, the user can link their Fitbit or Garmin account to Healthentia to start providing activity and sleep data.

Additionally, they can report various symptoms and events and will be able to regularly answer questionnaires related to their overall health status. After sufficient data has been collected for a particular user, the Healthentia platform will start to offer its inference services. Depending on the specific study configuration, this inference can be e.g., a prediction of future health status. The predictions that are made in an online fashion serve as input to a virtual coaching component – a conversational agent that can discuss the prediction with the user in natural language dialogues.

A healthcare professional is interested in grouping their patients to handle them. Generative models are learnt to describe the derived clusters of patients. The models corresponding to clusters that healthcare professionals find meaningful are termed phenotypes. Patients are then grouped into those clusters based on the similarity of their data to the different generative data, a process called phenotyping.

A data engineer is interested in working with Healthentia data. To do so, data is synthesized from the generative models.

3.2.2 Design & Specifications

The goal of the eHealth use case is thus to demonstrate the benefits of the PHYSICS FaaS approach on three scenarios:

- Inference for patients
- Patient phenotyping
- Data synthesis

To implement all three of them, several use case specific functional requirements have been derived, as shown in Table 2. These functional requirements are used as practical goals for the development of the first prototype described in Section 4.2 and as indications of its progress.

Table 2: Functional requirements for the eHealth use case.

Code	Functional Requirements
FRS-UC2-01	Service must be provided to be invoked by third parties
FRS-UC2-02	The services are to be deployed according to the principles of the PHYSICS project through OpenWhisk
FRS-UC2-03	The services are to be utilized via the endpoints exposed by functions deployed from Node-RED flows
FRS-UC2-04	The flows will utilize ML scripts written in Python
FRS-UC2-05	The ML scripts are to be invoked by specifying the model(s) to be used and if applicable, the vectors to infer upon

The fulfillment of these requirements in the current implementation of the eHealth use case is discussed in Section 4.2.

3.3 Use Case: “Smart Agriculture”

3.3.1 Synopsis

The smart agriculture pilot aims to provide growers enhancing greenhouse management scenarios. To achieve this goal, it is necessary to have: 1) A reliable tool to gather data collected in the greenhouse; 2) high performing simulation and optimization; 3) Up-to-date agronomic model parametrization obtained through calibration on empiric measurements. Figure 5 shows a global overview of the CybeleTech solution for greenhouses.

D6.4 (Franke, et al., 2022) provides all details and requirements for this Use Case. To better understand the provided functional specifications and prototype description (see section 4) we include a summary of a typical usage scenario here.

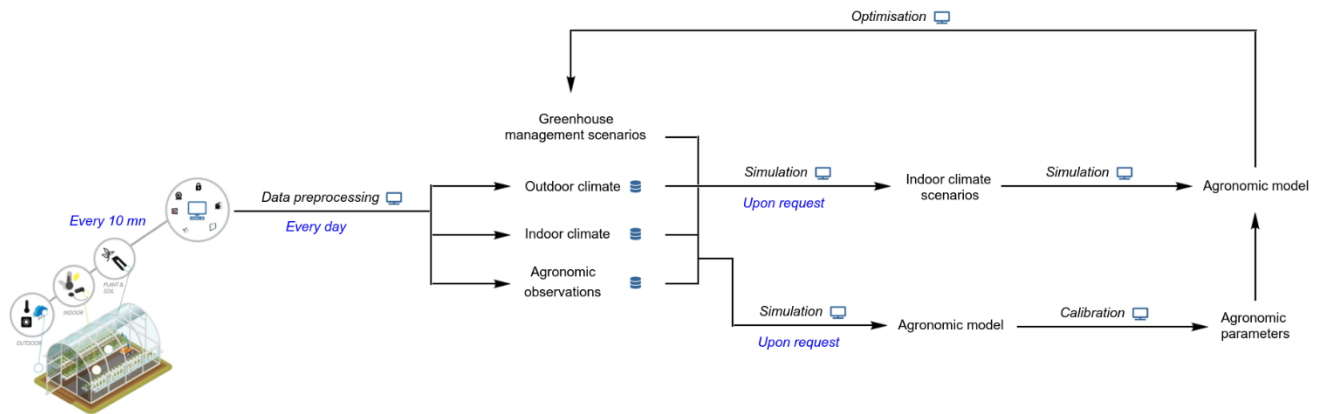


Figure 5: Overview of the Cybeletech solution for greenhouses.

Growers interested in monitoring plant development in their greenhouses and in improving the management of the environmental conditions will contact Cybeletech. Cybeletech will audit the computer infrastructure, adapt the solution to the greenhouse constraints and deploy it. Once Cybeletech's solution is deployed in the greenhouse, the data collected by greenhouse sensors are automatically retrieved, preprocessed, and stored in Cybeletech databases. The grower can visualize these data through the Cybeletech platform in near real time (NRT) to follow the environmental conditions in the greenhouse. Moreover, the system uses agronomic models developed by Cybeletech to give an overview of the plant status (e.g., healthy, heating of the leaves, water stress) in NRT. On the other hand, the grower can provide greenhouse management scenarios. Dedicated statistical models are then used to convert these scenarios in environmental conditions, which are in turn used to simulate plant development. Finally, the growers can ask for optimal greenhouse management scenarios. In this case, several scenarios are automatically generated and the best scenarios according to the tradeoff between plant development and environmental cost are returned.

3.3.2 Design & Specifications

The goal of the smart agriculture use case is thus to demonstrate: 1) how PHYSICS components can be deployed and used in the context of fog computing; and 2) the benefits of the PHYSICS FaaS approach on NRT simulation of plant development and optimization of greenhouse management. To achieve this, several use case specific functional requirements have been derived, as shown in Table 3.

Table 3: Functional requirements for the Smart Agriculture use case.

Code	Functional Requirements
FRS-UC3-01	A data collection pipeline that takes as input the Python script for data pre-processing must be provided.
FRS-UC3-02	The data collection pipeline is triggered automatically at regular time step and store data locally when connection is lost.
FRS-UC3-03	A minimal version of the docker image allowing to run the data collection pipeline is built during the deployment phase and can be pull from the edge.
FRS-UC3-04	A simulation / optimization flow must be provided to be invoked by Cybeletech greenhouse management suite.
FRS-UC3-05	The simulation / optimization service is to be deployed according to the principles of the PHYSICS project through the OpenWhisk platform.
FRS-UC3-07	The optimization service must take advantage of parallelization

As the first prototype, the emphasis was on adapting the pipeline for data collection. The fulfillment of these requirements in the current implementation of the Smart Agriculture use case is discussed in Section 4.3.

4 PROTOTYPE DESCRIPTIONS

4.1 Use Case “Smart Manufacturing”

Based on the BPMN diagram presented in Section §3.1.2, a flow was designed with the PHYSICS design environment in Node-RED as shown in Figure 6. This flow contains two OpenWhisk (OW) Actions: 1) Quality Control, 2) Complex Quality Control. OW Action (1) the same quality control as in “as-is” scenario – packaged as a custom OW Action-compatible docker-container. The OW Action (2) performs, as the name suggests, a more complex quality control requiring GPU acceleration. Both OW Actions contain proprietary code and AI models developed prior to PHYSICS project and thus will not be disclosed. The actions just encapsulate those to be usable within PHYSICS platform following its requirements and are imported to PHYSICS with the “Custom Image Upload” functionality.

4.1.1 Quality Control PHYSICS Flow

The flow starts after it receives a base64-encoded image data in JSON-format through a POST request to “/run” (standard interface for any OpenWhisk function). An example of the request can be seen in Code Snippet 1. Apart from the base64-encoded image, it also contains the expected product configuration depending on the customer order.

```
{
  "mime": "image/jpeg",
  "encoding": "base64",
  "image": "base64-encoded input image",
  "expected": [
    {
      "name": "UsbPenDrive 2x4 Blue",
      "type": "USB-PenDrive",
      "color": "blue",
      "size": "2x4",
      "horizontal position": 0,
      "vertical position": 0
    },
    {
      "name": "FlatStone 2x4 Black",
      "type": "FlatStone",
      "color": "black",
      "size": "2x4",
      "horizontal position": 0,
      "vertical position": 1
    }
  ]
}
```

Code Snippet 1: Example JSON input for the quality control inference service.

After each quality control operation, the certainty of the results is checked. An example output is given in Code Snippet 2. Apart from the processed base64-encoded image, it contains the Object Detection results (bounding boxes, labels, and confidence of prediction) for each object as well as the time taken in milliseconds for performance measurement purposes.

```

{
  "complex": true,
  "encoding": "base64",
  "image": "base64-encoded output image"
  "mime": "image/jpeg",
  "results": [
    {
      "confidence": 0.9248585104942322,
      "label": "UsbPenDrive 2x4 Blue",
      "x0": 2,
      "x1": 778,
      "y0": 687,
      "y1": 877
    },
    {
      "confidence": 0.9240514039993286,
      "label": "FlatStone 2x4 Black",
      "x0": 0,
      "x1": 777,
      "y0": 413,
      "y1": 701
    }
  ],
  "time taken": 0.66082,
  "version": "1.3.0"
}

```

Code Snippet 2: Example JSON output for the quality control inference service.

The resulting array scores are inspected, and the minimum confidence of all results is used for “certainty”. Based on the threshold, in the following manner:

1. After simple QC
 - a) If certainty is above the threshold, the quality result is checked,
 - b) If certainty is below the threshold, the image data is forwarded to complex QC.
2. After complex QC
 - a) If certainty is above the threshold, the quality result is checked,
 - b) If certainty is below the threshold, a manual inspection will be required.

Based on the conditions written above, three different status codes are generated. The computation results are summarized in Table 4.

Table 4: Summary of Status Codes of Use Case #2 in Smart Manufacturing Pilot.

	Quality OK	Quality Not OK
Certainty OK	AlloK	Certainty OK, Quality Not OK
Certainty Not OK	CertaintyNotOK	

If certainty is not OK, the operator will be notified by the caller of the Node-RED flow.

Figure 6 shows a prototype of the second scenario of manufacturing use case depicted in BPMN diagram (See Figure 3). The two “Dynamic simple/complex QC action” nodes are used to call the actual QC functions (custom images) dynamically via PHYSICS “Dynamic OW action”. The sub flow “QC – Check Certainty” checks whether the certainty is above the threshold. The “Check Results” sub flow checks whether the results of the QC function match the expected product parts. Sub flows were used for reusability and status reported for debugging. Note that the notification of the operator is handled outside of this flow.

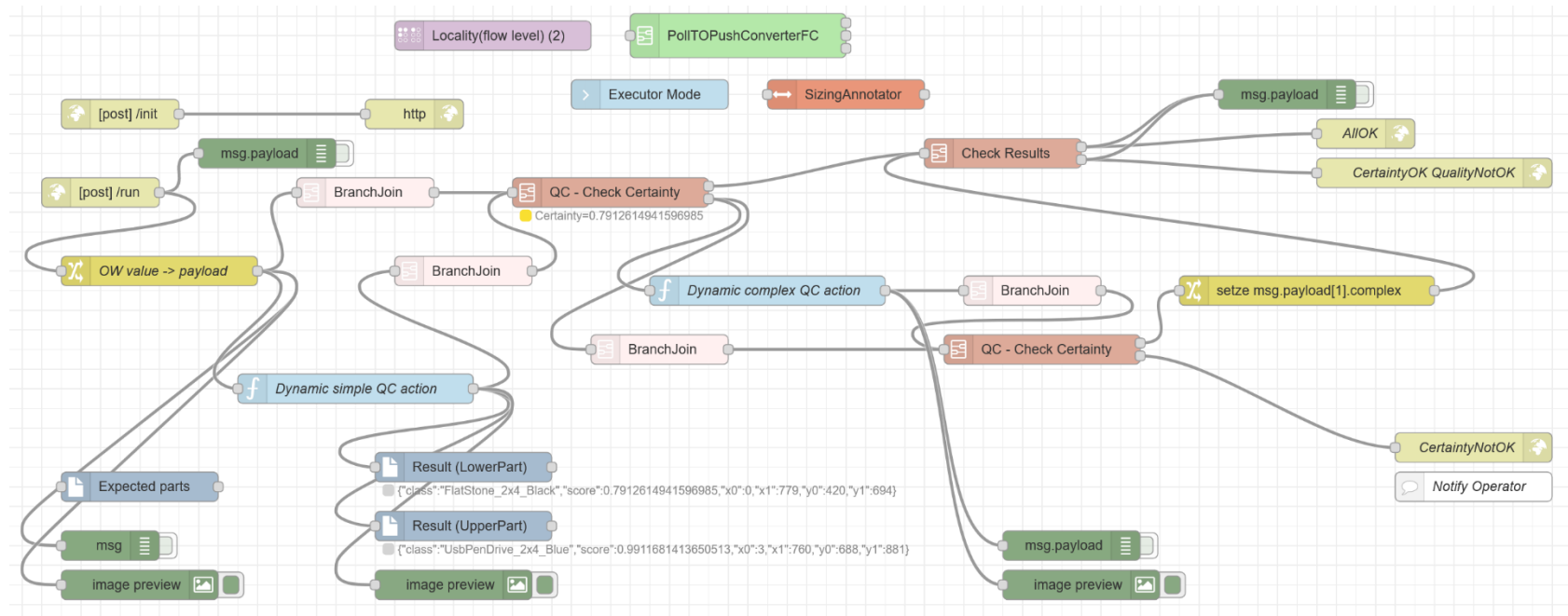


Figure 6: Smart Manufacturing Scenario #2, Final QC Node-RED Flow.

In Figure 7, the “QC - Check Certainty” sub flow is shown. It needs both the original message and the quality check result message, but Node-RED does not support nodes with multiple inputs, hence the *join* node is used for working around that limitation. Status is red if an error occurs, yellow if certainty is below the threshold and green otherwise.

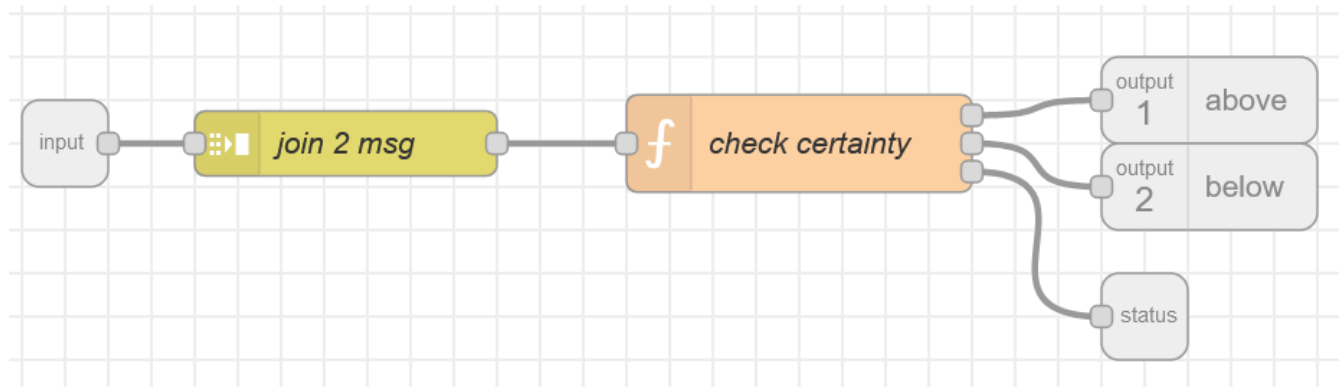


Figure 7: “QC - Check Certainty” sub flow.

The “Check results” sub flow is illustrated in Figure 8. The status is red if an error occurred, yellow if quality is not OK and green if it is OK.

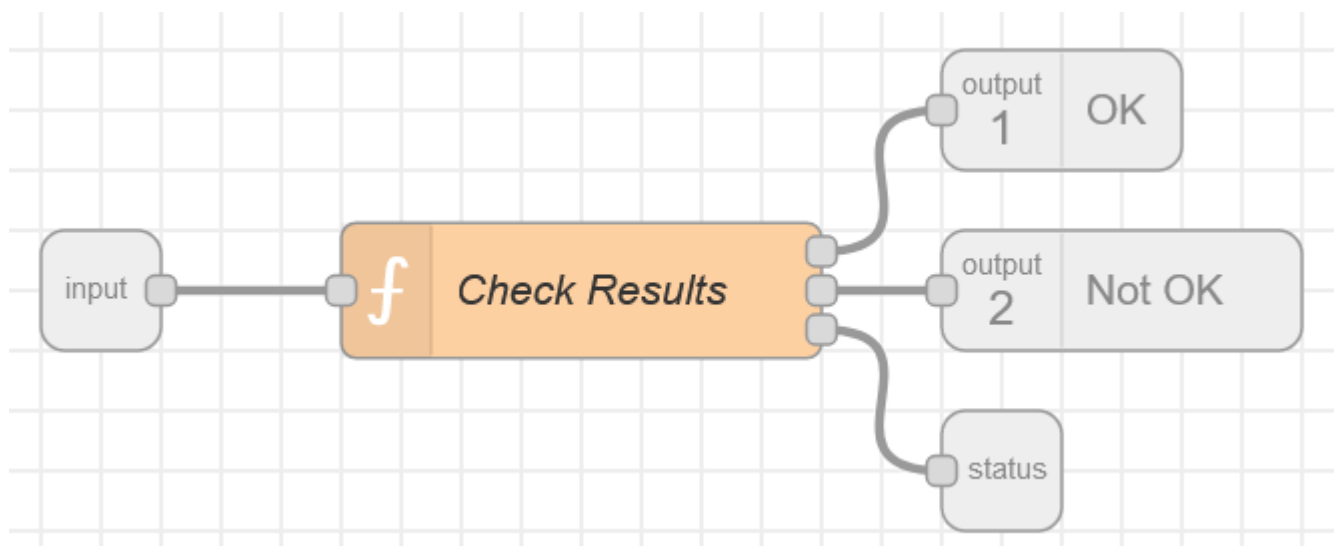


Figure 8: “Check Results” sub flow.

4.1.2 Fail-Over PHYSICS Flow

The complete Quality Check function discussed in section 4.1.1 is deployed both on the local edge instance of PHYSICS as well as in the cloud. The flow deciding which instance to use is shown in Figure 9. The “Edge OW MONITOR AND LOGGER” PHYSICS component monitors the local OpenWhisk instance. The “Router” PHYSICS component uses this information to route incoming requests according to its configuration. It is setup such that if the edge instance is not available or overloaded, the cloud instance is used instead (see in Figure 10). Further information about the router component can be found in Deliverable D3.2 Section 4.12. Because the OW monitor needs to run constantly, this flow is deployed as a service rather than a function.

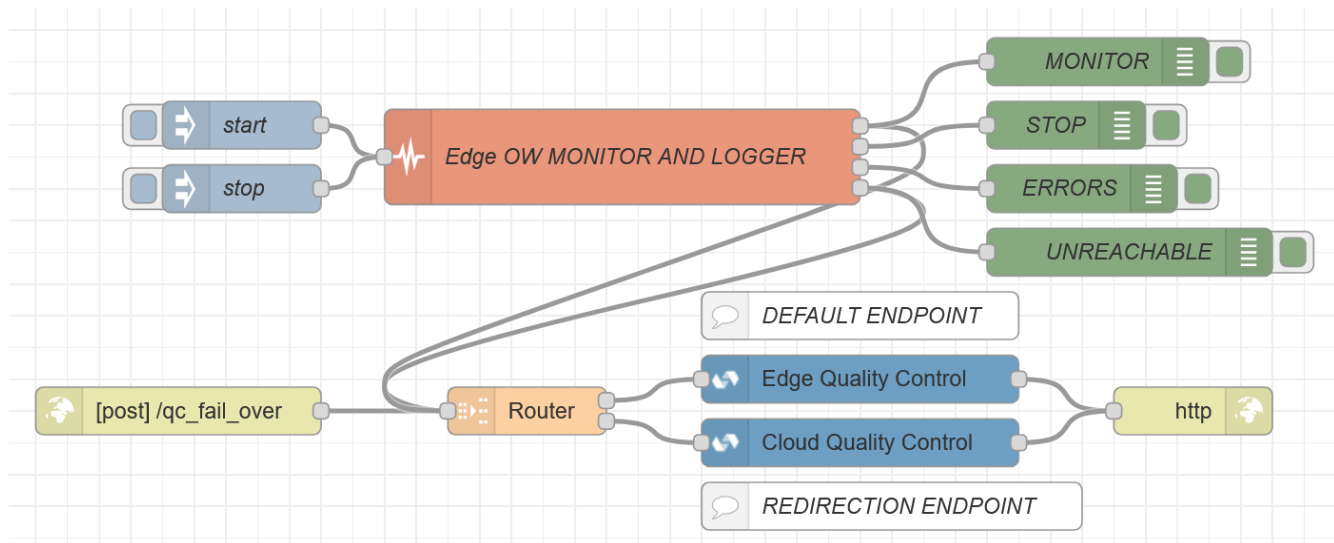


Figure 9 Fail-Over flow for Smart Manufacturing Use Case.




 Name	<input type="text" value="Name"/>
redirectionMetric	<input type="text" value="waitTime"/> ▼
redirectIfLarger	▼  true ▼
redirectionValue	▼  1000
strategy	<input type="text" value="fallBack"/> ▼

Figure 10 Fail-Over Router setup for Smart Manufacturing Use Case.

4.1.3 Concluding remarks

The source material for the prototype described here can be found on the internal PHYSICS repository:

<https://repo.apps.ocphub.physics-faas.eu/PHYSICS/test/src/dfki>

Access to this repository is limited to members of the PHYSICS Consortium but may be granted upon request.

Based on the prototypes and the functional requirements defined in section 3.1.2, a summary of fulfilment statuses of the requirements is shown in Table 5.

Table 5: Fulfillment of the functional requirements for the Smart Manufacturing use case.

Code	Functional Specification Fulfilment
FRS-UC1-01	Fulfilled. Endpoint is available at Kubernetes cluster with POST to “/qc”.
FRS-UC1-02	Fulfilled. Final version of Node-RED flows and quality control inference as OW-Action deployed.
FRS-UC1-03	Fulfilled. Integrated into the Node-RED flows.
FRS-UC1-04	Fulfilled. The inference takes place in a custom docker-based OpenWhisk action.
FRS-UC1-05	Fulfilled. Two separate functions for simple and complex QC are used instead of specifying the model.
FRS-UC1-06	Fulfilled. Both edge and cloud PHYSICS deployments use identical functions. Fail-Over is implemented using the PHYSICS Router Pattern.
FRS-UC1-07	Fulfilled. PHYSICS Router is setup to prefer edge deployment unless it is not available or overloaded.

The smart manufacturing use case has successfully fulfilled the respective functional requirements. Several components of the PHYSICS platform are utilized to exploit the FaaS benefits.

4.2 Use Case “eHealth”

The eHealth use case is utilizing a local deployment of the PHYSICS design environment to prepare the necessary flows, and then invokes their version deployed on OpenWhisk to run inference on healthcare data, given pre-trained ML models. The use of the PHYSICS design environment to implement and build the inference flow and the use of Python for the actual inference script as discussed in Section 4.2.1. The experimentation that can currently be carried out is demonstrated in Section 4.2.2. This demonstration is followed in Section 4.2.3 by instructions on running and using the system, as well as by a description of how the necessary docker image is built. Finally, the fulfillment of the use case functional specifications is considered in the concluding Section 4.2.4.

4.2.1 The eHealth PHYSICS flow

Once the local implementation of the PHYSICS Design Environment is up and running, one can access the Admin Panel to see the flows exposed by Node-RED, as shown in Figure 11.

Selecting any of the flows allows the user to build the flow using Jenkins (see Figure 12) and then have the resulting image deployed at OpenWhisk, whereupon the flow is available for inference both from the Node-RED environment, but also via external invocation.

Selecting Node-RED from the menu, one accesses the Node-RED flow editor, where all the flows in the local implementation (in this case the flows of the eHealth use case) are loaded, together with the PHYSICS Node-RED components. This is shown in Figure 13.

Three of the flows of the editor correspond to the inference, phenotyping and synthesis cases. Each of those flows are divided in three sections. The annotations section on the top utilizes PHYSICS annotations to allow the user to add information on the behavior of the flow as deployed in OpenWhisk. The endpoints definition section defines the two endpoints exposed by the flow, adapted to the Openwhisk Action specification:

- POST init handles initialization and is currently a stub (empty top row sub-flow), and
- POST run performs the inference (middle row sub-flow).

At the heart of the run endpoint lies the “Infer with Python” execution node, invoking the Python inference script, passing it the command-line arguments prepared by the “Prepare CLA” (Command Line Argument) Javascript function node that manipulates the “message” object into the “cla” one. The “Prepare response” Javascript function node considers the standard and error output streams of the execution node, as they are concatenated together using the PHYSICS Branch-Join pattern. The configuration of all three nodes is shown in Figure 14.

Available Flows

Document ID	URL	Action name	Built date
63a0855a030be01a8924cd25	registry.apps.ocphub.physics-faas.eu/custom/ehealth:31	Infer_ehealth_7f2ab4ba-9e92-4d3b-9a57-22b9ea411609.json	12/10/22, 5:38 PM
63bc0d1404eabdc2ba1207be	registry.apps.ocphub.physics-faas.eu/custom/ehealth:34	Infer_ehealth_3fdd72e6-5a02-4b83-a76e-edc05356447a.json	1/9/23, 2:48 PM
63bd605704eabdc2ba1207c1	registry.apps.ocphub.physics-faas.eu/custom/ehealth:37	Infer_ehealth_c2d9851f-7325-4cd2-8dc6-6bda563ad080.json	1/10/23, 2:55 PM
640208689b34275cd2da7053	registry.apps.ocphub.physics-faas.eu/custom/ehealth:53	Infer_ehealth_2371c93-3981-4740-882e-b334f8466931.json	3/3/23, 4:47 PM
645257b045e8e857cf46e833	registry.apps.ocphub.physics-faas.eu/custom/ehealth:60	Infer_ehealth_a05c52ac-0763-49cc-b63a-e4ac5e80af8a.json	5/3/23, 3:46 PM
6454b1b845e8e857cf46e834	registry.apps.ocphub.physics-faas.eu/custom/ehealth:61	Infer_ehealth_b57e367a-16c6-4b96-a578-435e14076569.json	5/5/23, 10:35 AM
645bc03845e8e857cf46e837	registry.apps.ocphub.physics-faas.eu/custom/ehealth:63	Infer_ehealth_b57e367a-16c6-4b96-a578-435e14076569.json	5/10/23, 7:03 PM
646c50ad45e8e857cf46e83c	registry.apps.ocphub.physics-faas.eu/custom/ehealth:64	Infer_ehealth_b648075b-899c-472e-a0ac-20abdab9b69b.json	5/23/23, 9:43 AM

Version: 1.1.0

Figure 11: Admin Panel showing the flows exposed by Node-RED in the eHealth local workflow.

Jenkins

αναζήτηση

Aristodemos Pnevmatikakis

Dashboard > test-BUILD > #358

Back to Project

Status

Changes

Console Output

Edit Build Information

Delete build '#358'

Parameters

Timings

Git Build Data

Replay

Pipeline Steps

Workspaces

Previous Build

Build #358 (23 Μαΐ 2022, 9:09:45 π.μ.)

Keep this build forever

Προσθήκη περιγραφής

Started 2 days 0 hr ago
Took 5 min 18 sec

Το ξεκίνησε ο χρήστης [Aristodemos Pnevmatikakis](#)

This run spent:

- 6.7 sec waiting;
- 5 min 18 sec build duration;
- 5 min 25 sec total from scheduled to completion.

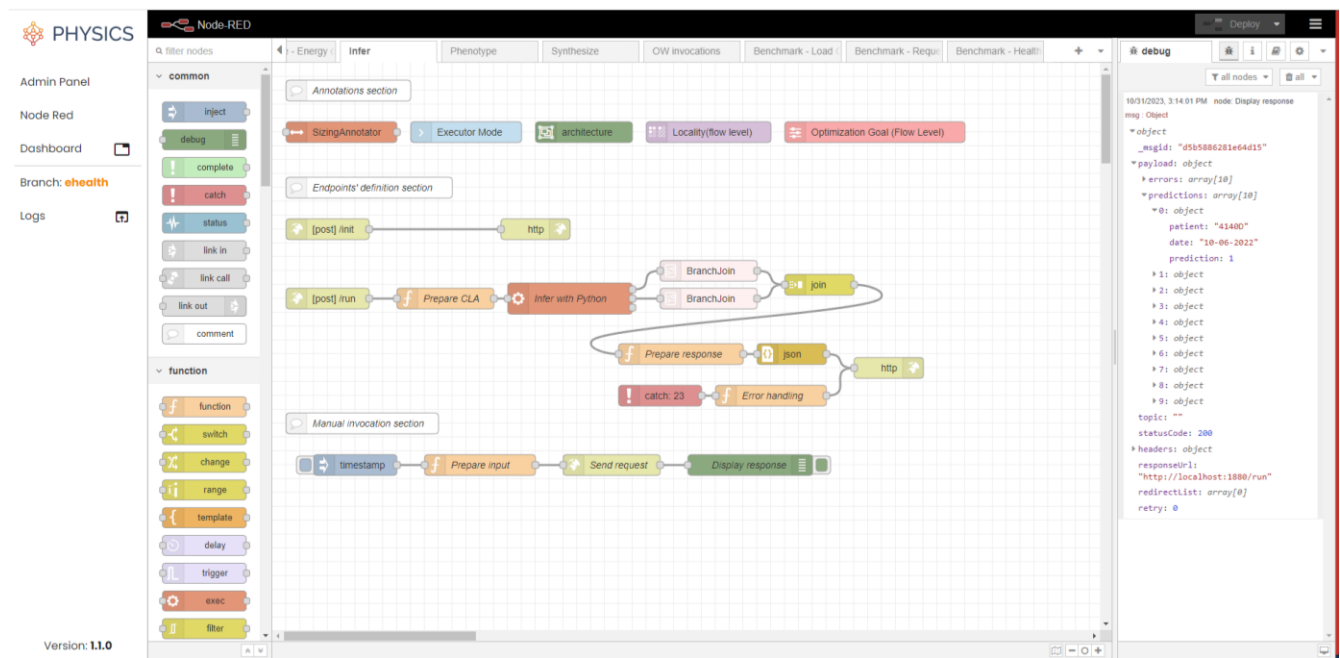
git Revision: 10e71ee4a45ade39454e23afc4df8009179f92b
Repository: <https://repo.apps.ocphub.physics-faas.eu/PHYSICS/test.git>

- refs/remotes/origin/master

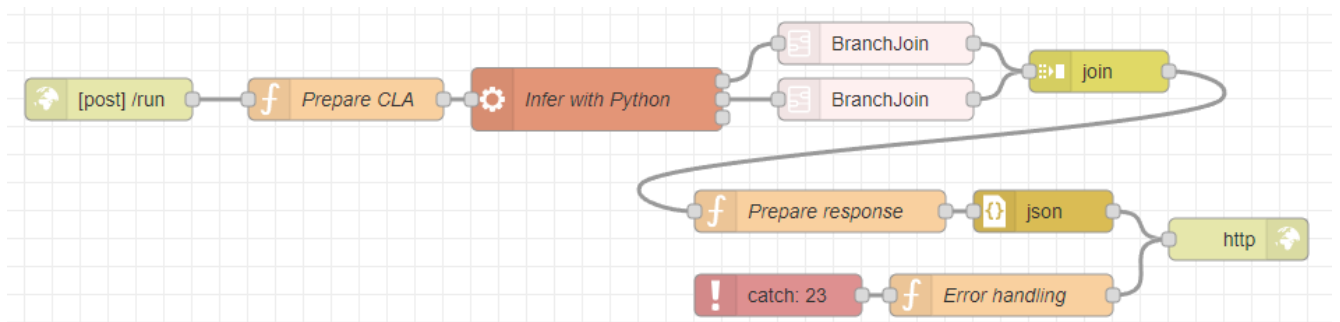
The following steps that have been detected may have insecure interpolation of sensitive variables ([click here for an explanation](#)):

- sh: [JENKINS_PASSWORD]
- sh: [JENKINS_PASSWORD]
- sh: [MINIO_KEY, MINIO_SECRET, JENKINS_PASSWORD]
- sh: [JENKINS_PASSWORD]

Figure 12: Jenkins build job initiated by the PHYSICS design environment (Admin panel) for the inference flow.



(a)



(b)

Figure 13: Node-RED interface depicting in inference flow in the eHealth local implementation (a) and zoom in the main flow (b).

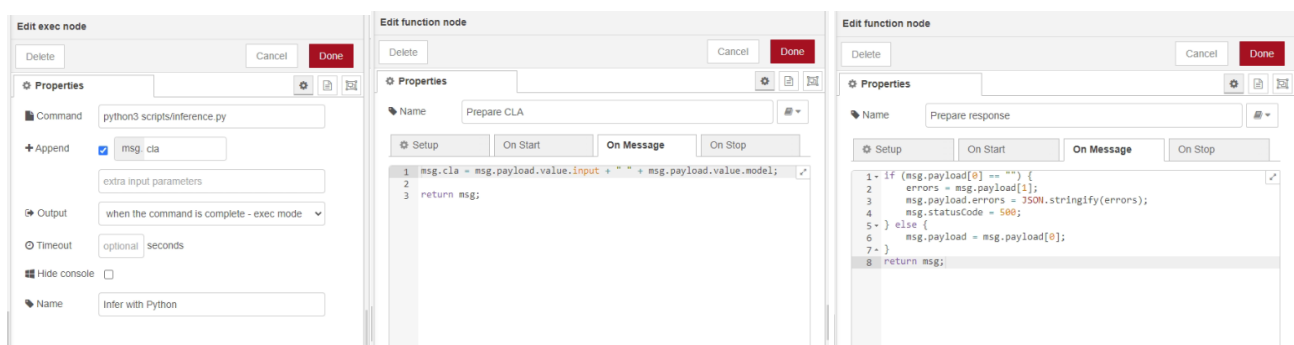


Figure 14: Properties of the “Infer with Python” execution node (left), the “Prepare CLA” function node (middle) and the “Prepare response” function node (right).

The manual invocation section of the flows, as well as the OW inference flow are considered in the experimentation section.

4.2.2 Experimentation on the eHealth PHYSICS flows

Any of the three flows can be executed within the Node-RED environment by manually activating the timestamp node in the manual invocation section of each flow. This is quite useful for debugging the flow at the creation stage, without having to undergo the OpenWhisk deployment phase.

The inference flow expects two input parameters: the input vectors to infer upon (given in `msg.payload.value.input`), and the name of the model to be used (given in `msg.payload.value.model`) for inference in the `inference.py` Python script. The JSON string to be passed to `msg.payload.value.input` for the inference is as follows:

```
[
  {
    "patient": "4140D",
    "date": "10-06-2022",
    "vector": [-0.1756308, 0.3731949, 0.2202068, 0.8069529, -0.1448357, 0.8299854, -0.3774286,
              1.6622097, -0.6561496, -0.1429273, -0.3793805, 0.7972746, 0.1187435, -0.0117112, 0.3693147]
  },
  ...
]
```

This outputs the inferences, one per provided vector. A second Python script, `inference_test.py`, is provided that also tests the inference using the known inference results, providing the classification accuracy.

Manually invoking the POST run of the flow results in successful inference as indicated by the inference results at the logs shown in the right column of Figure 13.

The phenotyping flow expects the input vectors to be phenotyped and the name of the joblib file containing all the generative models to compare each vector against. The synthesis flow expects the joblib file with the generative models, an array of the initial phenotype of each of the synthetic patients (the length of the array thus determines the number of synthetic patients), the number of time steps to infer for each synthetic patient and the phenotype transition probability matrix.

Any flow deployed in OpenWhisk can be executed by POSTing at its init and run endpoints from outside the PHYSICS design environment, or within an OpenWhisk experimentation flow. This is the OW inference flow, shown in Figure 15.

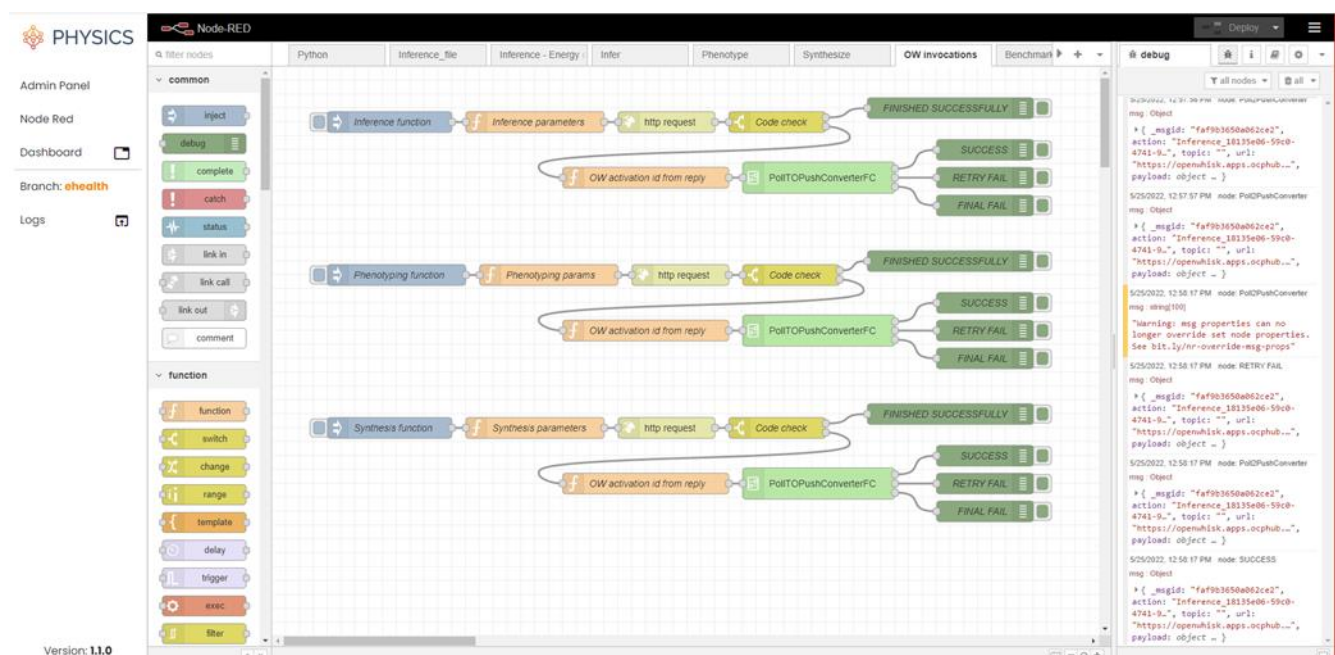


Figure 15: The OpenWhisk experimentation flow for the deployed flows of the three cases.

The flow is designed for manual-only invocation via any of the three inject nodes “Inference function”, “Phenotyping function”, or “Synthesis function”, where the respective deployed action name is given. The user can find this action name in the Jenkins build. The POST URL is reconstructed from this action name, and the expected parameters of the endpoint are given in the “Action invocation url” Javascript function. The log of executing the deployed flow is shown on the right column of Figure 15, where the final success is indicated.

4.2.3 eHealth use-case local design environment instructions

This section provides the installation and usage instructions for the local PHYSICS design environment for the eHealth use case. The system can be found in the ehealth branch of the PHYSICS Design Environment project in Gogs.

<https://repo.apps.ocphub.physics-faas.eu/PHYSICS/test/src/ehealth>

Access to this repository is limited to members of the PHYSICS Consortium but may be granted upon request.

A screenshot of the repository is shown in Figure 16.

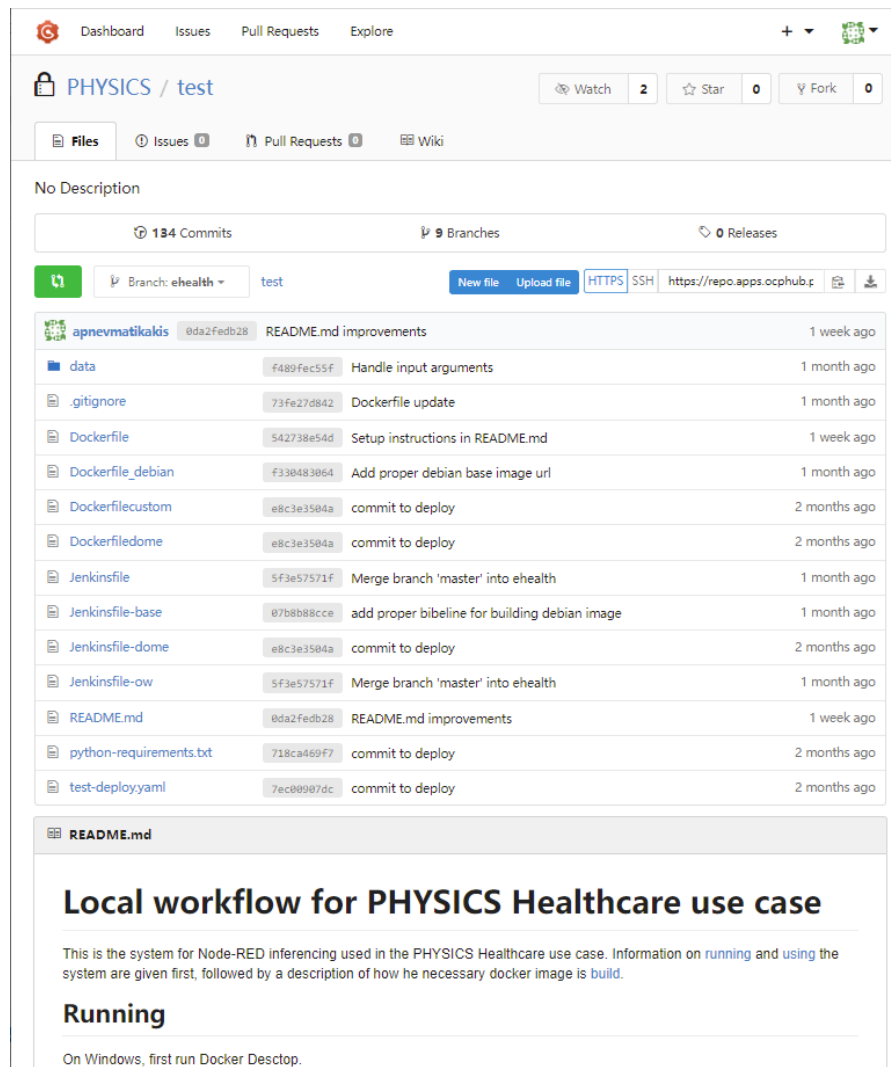


Figure 16: Screenshot of the Gogs eHealth repository.

To run the adapted PHYSICS Design Environment for the eHealth use case locally, first pull the repository in an ehealth directory. Add to the parent of the ehealth directory two files. The `credentials.env` environment file should have a number of tokens defined, as given by the PHYSICS project (see Code Snippet 3).

```
JENKINS_USERNAME=XXX
JENKINS_TOKEN= XXX
GIT_NODE_RED_TOKEN= XXX
GIT_NODE_RED_PATH=/repository
MINIO_ACCESS_KEY= XXX
MINIO_SECRET_KEY= XXX
MONGODB_PASSWORD= XXX
MONGODB_USER= XXX
JENKINS_PIPELINE_TOKEN= XXX
API_KEY= XXX
```

Code Snippet 3: Example `credentials.env` file with the required tokens to run the eHealth inference system.

The `docker-compose.yml` configuration file gives the information on how to build the three images of the system (see Code Snippet 4), namely the admin panel UI, the Node-RED and the SFG backend.

```
version: "3.9"
services:
  ui:
    container_name: ui
    image: registry.apps.ocphub.physics-faas.eu/design-environment/control-ui/design-environment-
    ui:latest
    ports:
      - "4200:4200"
  node-red:
    container_name: node-red
    build: ./<ehealth directory>
    volumes:
      - ./<ehealth directory>/data:/data
    ports:
      - "1880:1880"
  sfg:
    container_name: sfg
    image: registry.apps.ocphub.physics-faas.eu/design-environment/sfg/design-environment:latest
    volumes:
      - ./<ehealth directory>:/repository
    ports:
      - "3001:3001"
    links:
      - node-red
    env_file:
      - credentials.env
```

Code Snippet 4: `Docker-compose.yml` configuration file.

Where `<ehealth directory>` is replaced with the actual ehealth directory name.

Then run Docker Desktop. Open a terminal and:

- Go to the parent directory of the `<ehealth directory>`
- `docker-compose up --build`

The Node-RED image that is built also includes Python, the necessary libraries, the scripts for inference and the models. Details on using and building the system follow.

To use the system, go to `http://localhost:4200/` for the Admin Panel, or to `http://localhost:4200/node-red` for the Node-RED instance where the created flows are already loaded. After any useful modification of the flows, click on "Deploy" to actually store the changes in `data/flows.json`.

Deployed flows can then be built via the Admin panel (via Jenkins behind the scene) and be registered in OpenWhisk.

The Python scripts and the model data to be used in the flows are in `data/scripts`. In detail, the contents are:

- `requirements.txt`: It is used to setup the Python environment by installing the necessary libraries
- `*.py`: The different scripts to be used in the Node-RED flows
- `*.joblib`: Data to be used for inference and model metadata (complete model in the case of a Random Forest one)
- Neural Network models in directories

The Dockerfile found at the root of the project is used to set up the Node-RED and Python image needed for the use case. The starting point is the Debian image from the PHYSICS consortium:

```
FROM registry.apps.ocphub.physics-faas.eu/wp3/debian-base:latest
```

In there, as ROOT user, first the scripts directory is created and populated:

```
USER root
RUN mkdir -p /usr/src/node-red/scripts
COPY data/scripts /usr/src/node-red/scripts
```

Then Python is installed:

```
RUN apt install -y python3-dev python3-pip
RUN pip3 install --upgrade pip
```

To be followed by the 3rd party library requirements:

```
RUN pip3 install -r scripts/requirements.txt
```

Finally, the properties of the data folder are set and the working user is set to node-red:

```
RUN chown -R node-red /data
RUN chmod -R 775 /data
USER node-red
```

4.2.4 Concluding remarks

After having described the eHealth use case flows and the implementation of services from them, we now look back at the functional specifications that were defined in section 3.2.2. For each of the Functional Specifications, we discuss how the specifications are fulfilled. The fulfillment of the functional specifications introduced in Table 2 is discussed in Table 5.

Table 5: Fulfilment of the functional specifications for the eHealth use case.

Code	Functional Specification Fulfilment
FRS-UC2-01	Fulfilled. Three services have been generated from the respective flows, and URLs are provided for their invocation. Any 3 rd party system can utilize these URLs.
FRS-UC2-02	Fulfilled. Deployed flows can then be built via the admin panel, whereupon they are registered in OpenWhisk.
FRS-UC2-03	Fulfilled via the run endpoint exposed by the Node-RED inference, phenotyping and synthesis flows.

FRS-UC2-04	Fulfilled, since a Python script is provided for each of the three cases of interest (inference, phenotyping and synthesis). Specifically for inference, two scripts are provided, one just for inference and another for both inference and testing, to be used in the case the correct inference results are known.
FRS-UC2-05	Fulfilled: Each service requires its own set of parameters to be POSTed. These parameters are passed to the underlying Python scripts.

The eHealth use case has successfully fulfilled the respective functional requirements. Several components of the PHYSICS platform are utilized to exploit the FaaS benefits.

4.3 Use Case “Smart Agriculture”

4.3.1 Data collection pipeline

4.3.1.1 Pipeline definition using Node-Red

The pipeline is implemented as a Node-RED flow and packaged as a subflow (Edge ETL Service). The implementation appears in Figure 17. Initially an input is provided so that the developer can plug in any kind of means to obtain the primary data value, encapsulated in the payload field of the message. Then any custom ETL logic can be applied through one or more functions and apply any needed transformation, filtering, or other operation on the data. Once this is finalized, the generic part of the pattern begins. Given that any output nodes, such as the HTTP out node used in this example, may substitute the contents of the msg.payload field with the results of the call that pushes the data to the central system, it is necessary to maintain the original data for future use (in case the transmission fails). For this reason, these are moved in the "Keep contents" function in the msg.originalpayload field. This function is also responsible for inserting a retry counter in the message, as well as differentiating the origin of the message (new data that have arrived or past data that have failed and have been stored locally, see (Kousiouris, 2023) for more details).

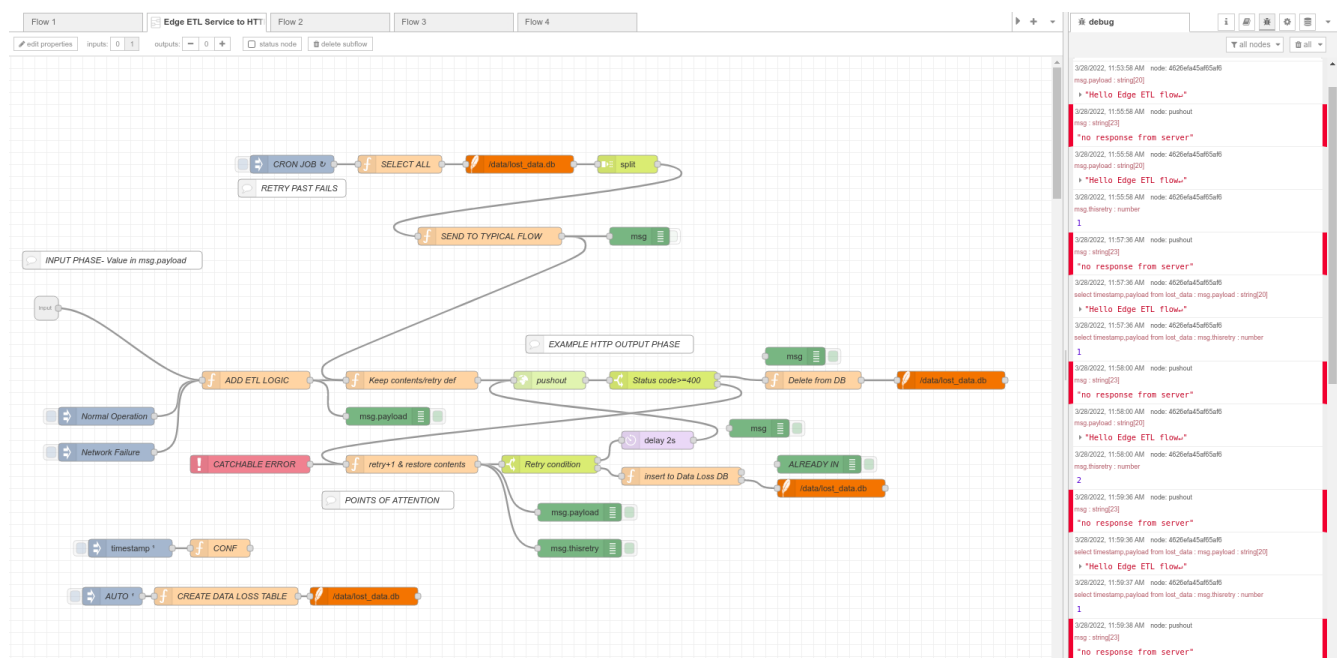


Figure 17: Implementation Flow for the Edge ETL Pattern.

Besides the adaptation of the Python script managing the parsing of the file containing the data collected by the sensors passed as an argument of the Edge ETL flow, some parameters must be defined including the

frequency of pipeline triggering, the number of retries before storage of data in the local database, and the authentication information for API connection to Cybeletech database (Figure 18).

4.3.1.2 Adaptation of legacy codes

According to the greenhouse supervisor specifications, the data collection logic must be adapted. As today Cybeletech application enables to deal with two types of supervisors.

One automatically generates a plain *.txt* file at regular time intervals. In this case a Python script is run at regular time intervals with a cron. This script:

1. Read the plain *.txt* file.
2. Perform preprocessing operations to ensure compliance between sensor data collected by the supervisor and Cybeletech data model.
3. Check the existence of the preprocessed data in Cybeletech database
4. Insert the data via a dedicated SQLite driver developed by Cybeletech if they are not already in the database.

In case of connection failure between the supervisor and Cybeletech server, the plain *.txt* file is archived and will be parsed the next time the script runs.

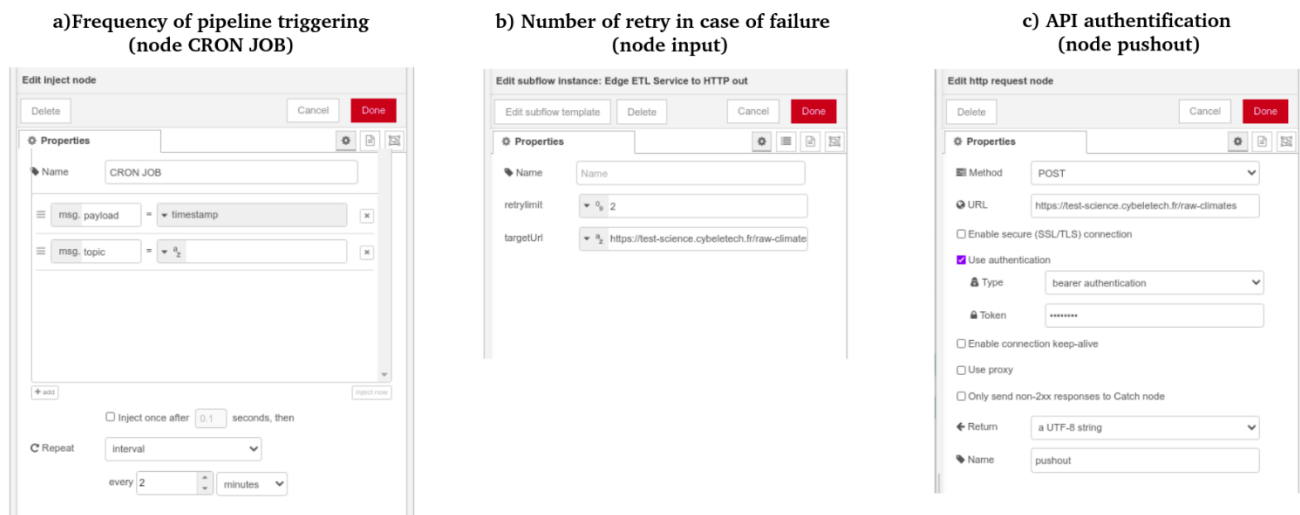


Figure 18: Settings of Node-RED ETL flow for data collection pipeline.

The other provides access to the data collected by the sensor via an API. In this case a Python script is run at regular time intervals with a cron. This script:

1. Send a request to the supervisor API.
2. Check if sensor data have been archived during the previous runs and read the archive files if they exist.
3. Perform preprocessing operations to ensure compliance between sensor data obtained with the API, and eventually from the archived files, and Cybeletech data model.
4. Insert the data via a dedicated SQLite driver developed by Cybeletech.

In case of connection failure between the supervisor and Cybeletech server the data obtained with the API are archived in a *.json* file, which will be parsed the next time the script runs.

During the adaptation phase the supervisor dependent part of the data collection logic has been extracted of the legacy codes and adapted so that it can be run using the Edge ETL Pattern.

Moreover, an API for data transfer from the supervisor to Cybeletech server has been developed so that the *http node* can be used.

Once this adaptation is implemented, the Python script can be passed as argument to the generic Edge ETL Pattern (see Figure 19).

As the data collection pipeline logic is defined in a generic pattern, it allows to decorrelate the part of the code dedicated to data gathering from the sensors and data preprocessing, from the part dedicated to the job running and connection failure management. This has considerably simplified the Python code base used for data collection and will ease their maintenance and adaptation to new contexts.

4.3.1.3 Pipeline testing using the design environment

The pipeline of data collection has been created and tested using the PHYSICS Design Environment. For this test the Python script performing data parsing and a .txt file such as those produced by the supervisor of type 1 have been uploaded in the /data repository of the test project. This repository is shared with the docker container hosting the Design Environment and allows the use of scripts and data in the Node-RED flows.

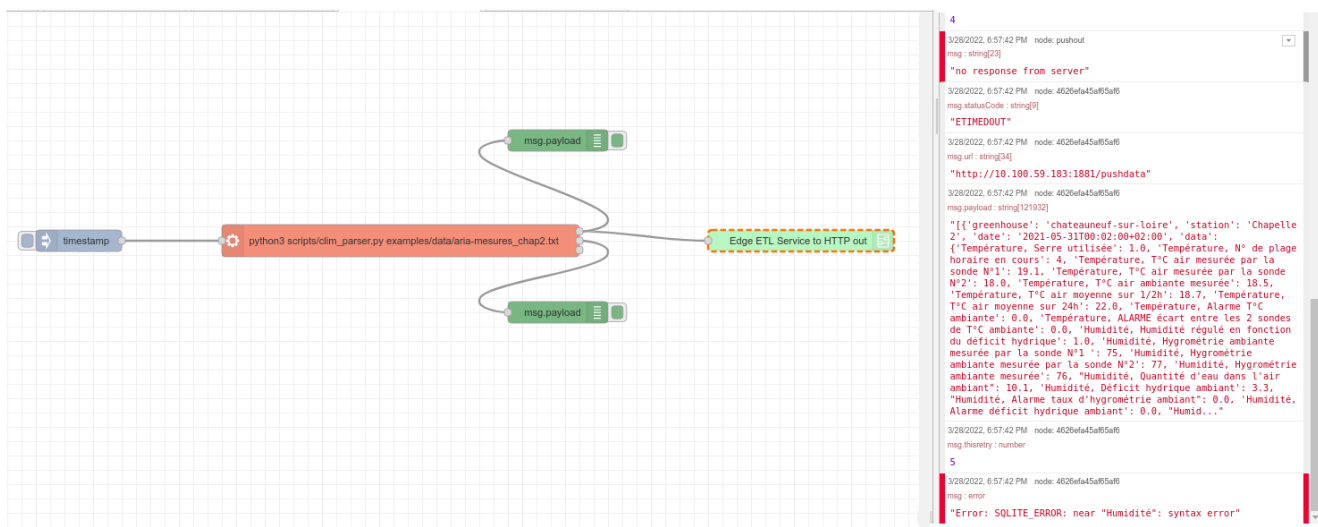


Figure 19: ETL flow testing.

Three scenarios have been tested:

1. In the first scenario it was assumed that no connection failure occurs during the data collection procedure. It validates the integration of the Python script in the Edge ETL Pattern and the configuration of the nodes.
2. In the second scenario it was assumed that temporary connection failure occurs during the data collection procedure. It validates that the retry procedure allows to overcome transient connection troubleshooting.
3. In the third scenario it was assumed that extended connection loss occurs during the data collection procedure. It validates that while the API cannot be reached the data are stored locally with no duplicate and that these data are sent to the distant database as soon as the connection is restored.

The outcome of the first scenario is presented in Figure 20. In this case the pipeline succeeded, and all the data collected by the sensors have been preprocessed and sent to Cybeletech database using the API at the first try.

b) Data sent using the API

[illegible]

The outcome of the second scenario is presented in Figure 21. In this scenario the pipeline failed three times, and at the fourth attempt, when the connection has been restored, data collected by the sensors have been preprocessed and sent to Cybeletech database using the API.

b) Node-RED debug message

[illegible]

In scenario 3 the pipeline failed five times, which is the maximum number of retries. The data is then stored in a local SQLite instance. After a while the pipeline is re-run and the data stored in the local database as well as the new data were sent to Cybeletech database.

4.3.2.1 Pipeline definition using Node-Red

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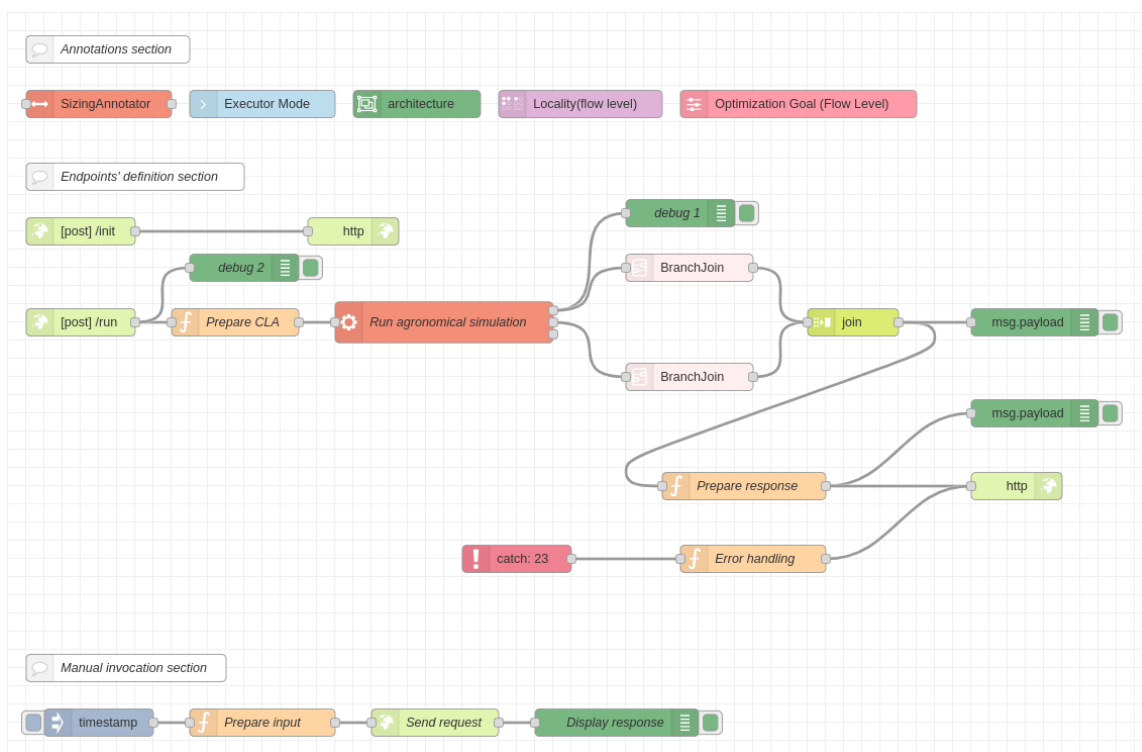
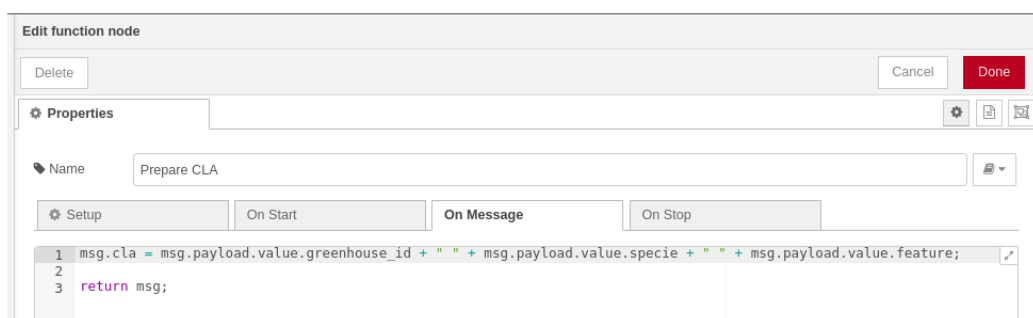


Figure 22: Node-RED flow describing the simulation pipeline.

A. Function node for input preparation



B. Function node for output preparation

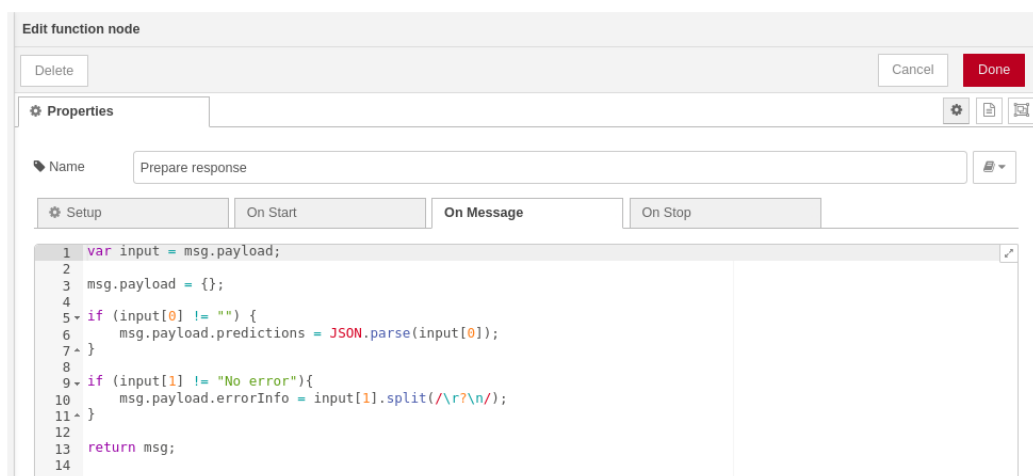


Figure 23: Node-RED function node for specification of I/O of simulation pipeline.

4.3.2.2 Adaptation of legacy codes

The integration of the Python script in the Node-RED flow is straightforward. The main change introduced is the adaptation of the input / output management: the inputs are collected using the `sys` module, which enables to get the command line arguments passed to the python script; the output is formatted as a json string and returned using the standard output channel (Figure 24).

Moreover, we introduced the use of the `logging` module to collect the logs of the script execution. This allows us to write info, warnings and errors in the standard error channel and to collect them at the end of the execution.

```

403
404 if __name__ == "__main__":
405
406     # Simulation setup
407     env = {
408         "AREA_FILE": "/usr/src/node-red/input_data/agro_models_setup.geojson",
409         "TARGET_CAMPAIGN": "2023",
410         "MODEL_DIR": "/usr/src/node-red/input_data",
411         "OUTPUT_DIR": "/usr/src/node-red/output_data",
412         "CLIMATE_FILE_DIR": "/usr/src/node-red/input_data",
413     }
414
415     # Collect input data from the command line arguments
416     env["ID_ZONE"] = sys.argv[1]
417     env["ID_SPECIE"] = sys.argv[2]
418     env["ID_FEATURE"] = sys.argv[3]
419
420     # Setup logging for writing in standard error
421     logging.basicConfig(level=logging.INFO)
422
423     # Run simulation
424     simulation_output = main(env)
425
426     # Format output
427     sys.stdout.write(json.dumps(simulation_output))
428

```

Figure 24: Adaptation of Python script for simulation pipeline execution.

4.3.2.3 Pipeline deployment and testing

First, the simulation pipeline has been tested locally using the Node-RED panel of the Design Environment. The manual invocation of the flow is done using the http request node with a specific URL. The preparation of the input message is done using the function node (Figure 25).

The different steps of the pipeline can be monitored using the debug nodes, which output messages in the debug window of the Node-RED user interface. In a typical run, the user provides the id of its greenhouse, the species grown and the properties of interest. The simulation script looks for model parameters according to the species and uses them to provide an estimation of the target properties according to environmental conditions in the greenhouse (Figure 26). Here the climate conditions and models' parameters are made available through plain files embedded in the docker image.

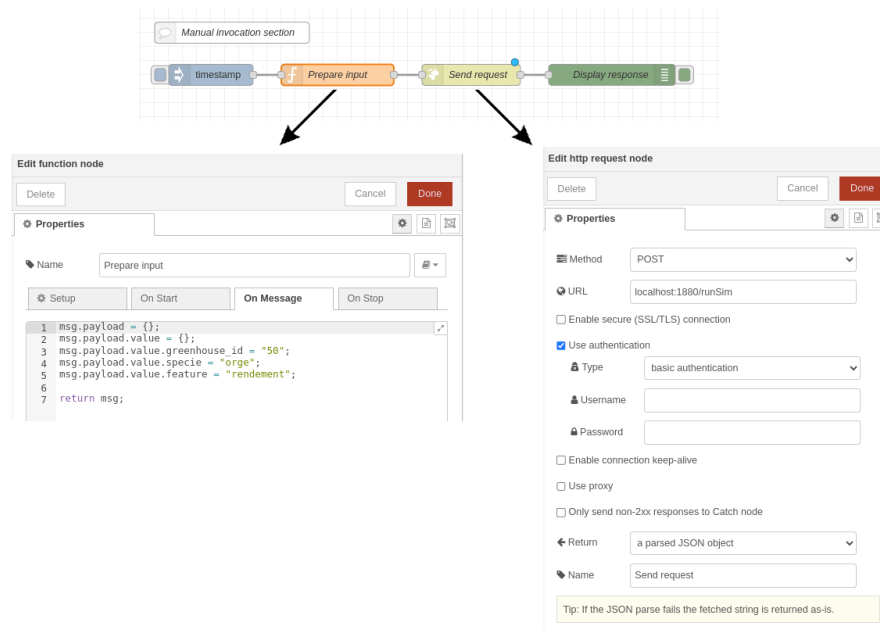


Figure 25: Adaptation of Python script for simulation pipeline execution.

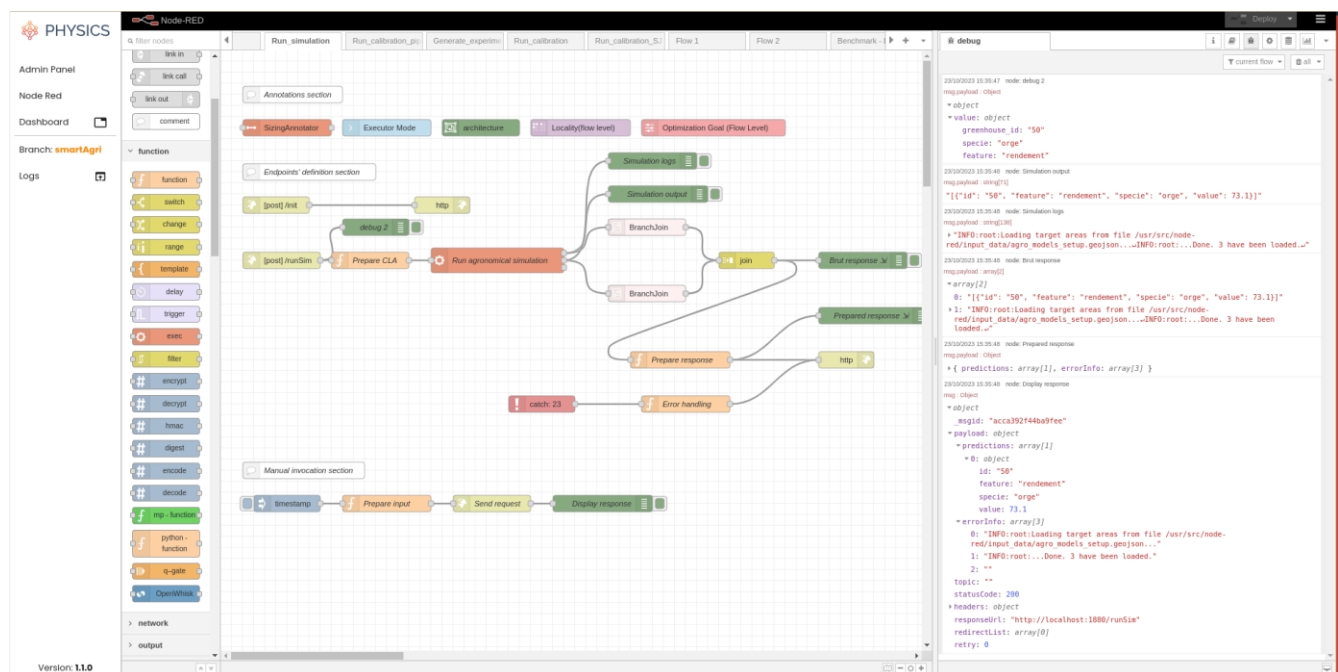


Figure 26: Local testing of the simulation pipeline using the Node-RED debug window.

Once the local tests passed, the simulation pipeline has been deployed using the admin panel of the Design Environment (Figure 27-A). The steps of the deployment process can be monitored using Jenkin (Figure 27-B).

A. Deployment of the simulation pipeline with the Design Environment

Available Flows

Document ID	URL	Action name	Built date
6480ee6e6d1a4a0846822c8	registry.apps.ocphub.physics-faoa.eu/custom/master-254	Run_simulation_master_dca199-oad5-47dc-928b-68f2c0a95d5.json	6/16/23, 12:58 PM
6480ee6e6d1a4a0846822c8	registry.apps.ocphub.physics-faoa.eu/custom/master-255	Run_simulation_master_ea94a0844-ac95-4942-0852-4822d17a9d5.json	6/16/23, 4:30 PM
6490c79761d4a0846822c8	registry.apps.ocphub.physics-faoa.eu/custom/master-256	Run_simulation_master_781b41a1-00de-4538-bafa-4a9532bdc96.json	6/21/23, 11:49 AM
650d323076181977056eab47	registry.apps.ocphub.physics-faoa.eu/custom/smartAgri2	Run_simulation_smartAgri_self5c5c-0892-4263-0450-1c30504781a3.json	10/4/23, 11:36 AM
650d323076181977056eab47	registry.apps.ocphub.physics-faoa.eu/custom/smartAgri3	Run_simulation_smartAgri_defef5c5c-0892-4263-0450-1c30504781a3.json	10/4/23, 12:19 PM
650d461076181977056eab49	registry.apps.ocphub.physics-faoa.eu/custom/smartAgri8	Run_simulation_smartAgri_self5c5c-0892-4263-0450-1c30504781a3.json	10/4/23, 1:01 PM
650d461076181977056eab49	registry.apps.ocphub.physics-faoa.eu/custom/smartAgri5	Run_simulation_smartAgri_7d577048-852d-471e-9200-73ca39349591.json	10/6/23, 2:56 PM

Jenkins build has started! [link to jenkins job](#)

B. Deployment monitoring using Jenkins

Pipeline smartAgri

Full project name: TEST-multi/smartAgri

Stage View

Testing condition	Check condition	Build Custom Image	Push Base Image	Build Custom Image	Push Custom Image	Trigger Deploy
64ms	837ms	2min 31s	1min 2s	0ms	26s	57s
160ms	837ms	2min 17s	1min 11s	58s		
36ms	1s	2min 25s	1min 11s	59s	28s	42s

Figure 27: Simulation pipeline deployment using the Design Environment (A) and deployment monitoring with Jenkins (B).

Once the deployment is completed, the Design Environment allows us to test the workflow as FaaS. The input of the pipeline can be specified via a form and the output is provided in a table when execution succeeds (Figure 28).

Function

Run_simulation_smartAgri_21703906-aa51-48c1-9108-74d7c80409ef.json

Put JSON for parameters

Parameter key *	Parameter value *
greenhouse_id	50
specie	orge
feature	rendement

Trigger

☒ Check automatically until success - requests: 9, updated at 4:15:52 PM

Check result

Activation ID: 1a55542a002f4b0095642a002eb00bc

Run_simulation_smartAgri_21703906-aa51-48c1-9108-74d7c80409ef.json

1a55542a002f4b0095642a002eb00bc

Params

feature	rendement
greenhouse_id	50
specie	orge

Result

errorinfo	predictions
[{"errorinfo": "Loading target areas from file /usr/src/node-red/input_data/agri_model_setup.geojson...", "errorinfo": "...done, a have been loaded.", "errorinfo": ""}]	[{"feature": "rendement", "id": "96", "specie": "orge", "value": 73.1}]

Figure 28: Local testing of the simulation pipeline using the Node-RED debug window.

Moreover, the admin panel provides access to detailed logs in which the debug messages defined in the flow are made available (Figure XX).

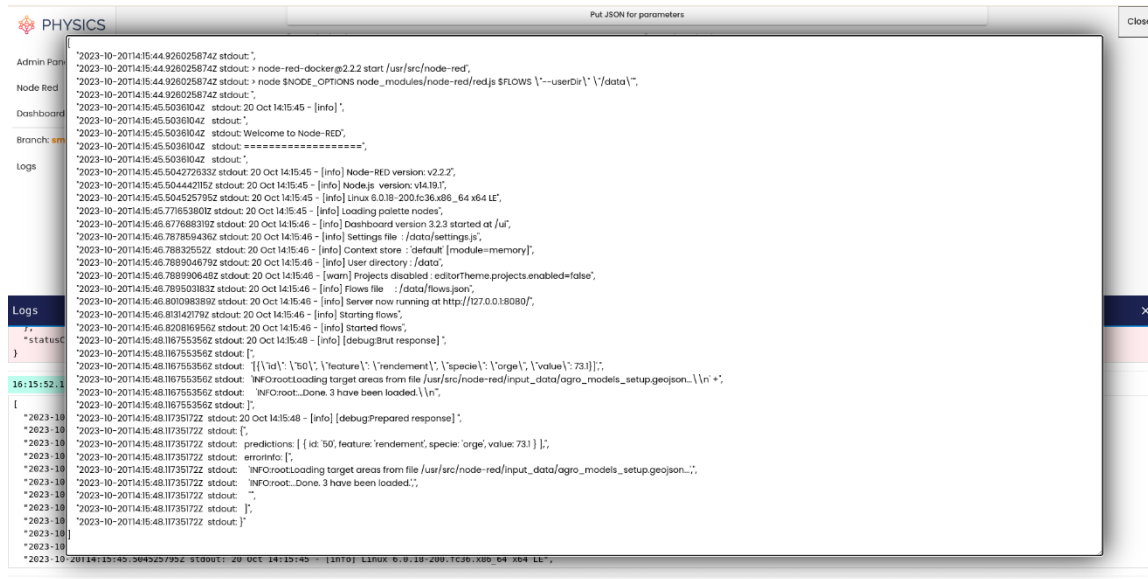


Figure 29: Local testing of the simulation pipeline using the Node-RED debug window.

4.3.3 Calibration pipeline

4.3.3.1 Pipeline definition using Node-Red

The pipeline is made up of three main steps:

1. Generation of a design of experiment. In its simplest form it consists of a grid where each node represents a model parameter set.
2. Running the simulation pipeline for each parameter set and evaluating the results regarding in situ observations.
3. Clustering of the model parameters set based on the evaluation with the objective of identifying groups of parameters sets which reproduce part or full plant behavior.

We propose three implementations for this pipeline:

1. The first implementation is used as a baseline for implementation and testing of the different components required. All the steps are embedded in one flow and the parameter set evaluations (step 2) are run sequentially.
2. In the second implementation we seek to take advantage of the FaaS approach by parallelizing the run of the simulation pipeline. All the steps are embedded in one flow and the parameter set evaluations are run in parallel using the split and join pattern.
3. In the third implementation we seek to integrate multi-processing at the function level: the parameter set evaluations will be distributed in FaaS mode as in the second implementation, but we add a level of parallelization with each function being able to distribute the evaluations over the processors available on the pod. This distribution is enabled by the split and join pattern with specific parametrization.

The first and third steps of the pipeline should not be parallelized since they are respectively input generation and output gathering and analyzing. The second step is highly parallelizable since each simulation can be run and evaluated independently from the others. In the first version of the flow each step is defined as an independent exec node triggering a dedicated Python script. The communication between the nodes is ensured by function nodes, writing the output of the previous node in the input field of the message retrieved by the current node (Figure 30).

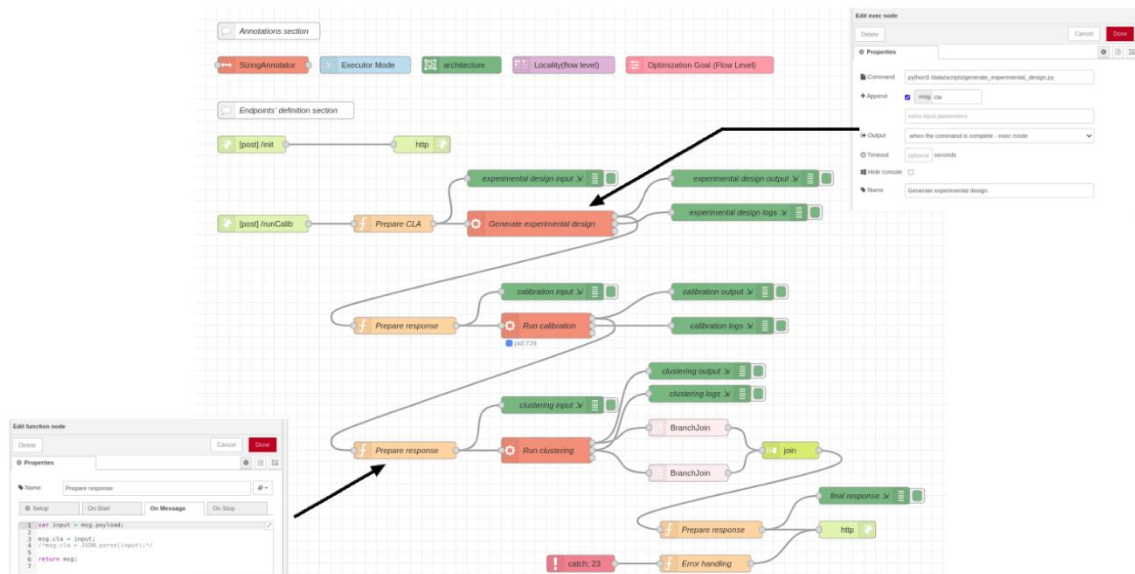


Figure 30: Node-RED flow describing the calibration pipeline.

To take advantage of the split and join pattern we first defined a dedicated parameter set evaluation flow which takes as input a vector with every element being a node of the design of experiment. The formatting of the input vector as a string is operated by a dedicated node. This input string is then decoded by the calibration script, implemented in Python and triggered using the exec node (Figure 31).

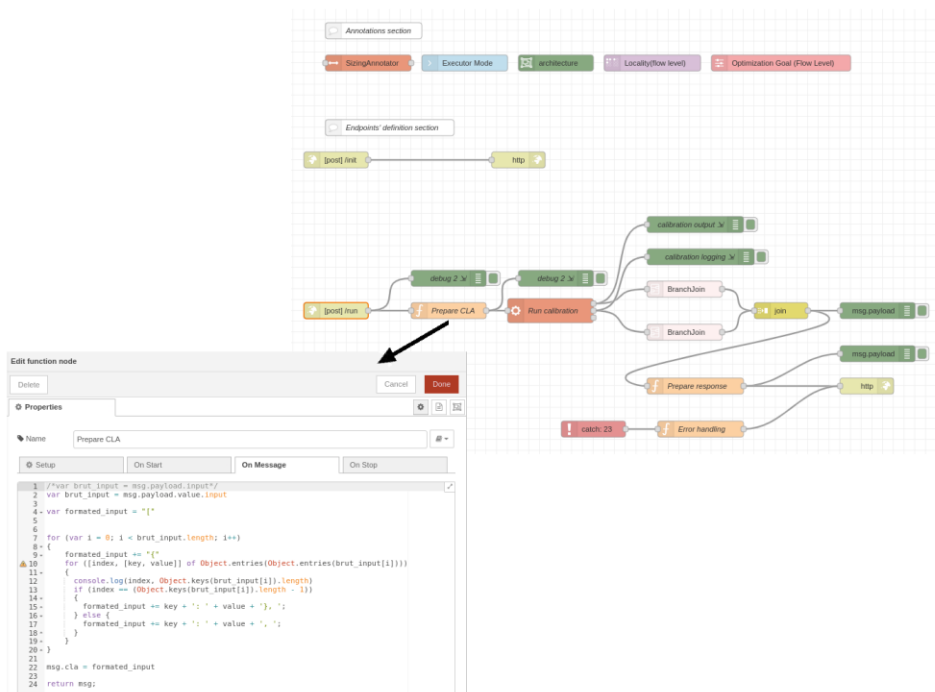


Figure 31: Node-RED flow allowing to run calibration from an array of nodes such as generated by the Python script for experimental design generation.

Then we can call this calibration flow using the split and join node. The routine allowing to prepare the input for the calibration flow from the message sent by the split and join node is embedded in the calibration flow (Figure 32). On the other hand, the output of the split and join node needs to be aggregated before being sent to the clustering node (Figure 32). The parametrization of the split and join node is

straightforward and can be done using the Node-RED UI. It required the URL of the function to run in parallel (innerActionURL field in the node setup) which in our case is described by the calibration flow and the number of splits to perform (splitSize field in the node setup).

The split and join pattern allow us to take advantage of FaaS approach to run the parameter set evaluation in parallel. This pattern also includes an option to distribute the evaluations over the processors of a server. In the third implementation of the calibration pipeline, we combine FaaS and multiprocessing.

To achieve this double parallelization, we adapt the dedicated parameter set evaluation flow used in the second version. The main difference lies in the calling of python script describing the parameter set evaluation procedure. In the second implementation the script was run using an exec node (see node called Run calibration, XXXXXX31) while here the script is run in parallel over the processors thanks to the split and join pattern. The parameterization of the split and join node is very straightforward with the command to run the script being specified through the Shell script field of the subflow. We also need to specify that we want to run it using multiprocessing (field execution of the subflow) and the number of evaluations we want to run on each processor (field splitSize of the subflow, Figure 33).

To ensure consistency between the FaaS and the FaaS-multiprocessing pipeline we added a formatting sequence after the split and join node.

To use the FaaS-multiprocessing version of the calibration pipeline we only need to change the innerActionURL field in the split and join pattern so that it points on the multiprocessing version of the parameter set evaluation function (Figure 32).

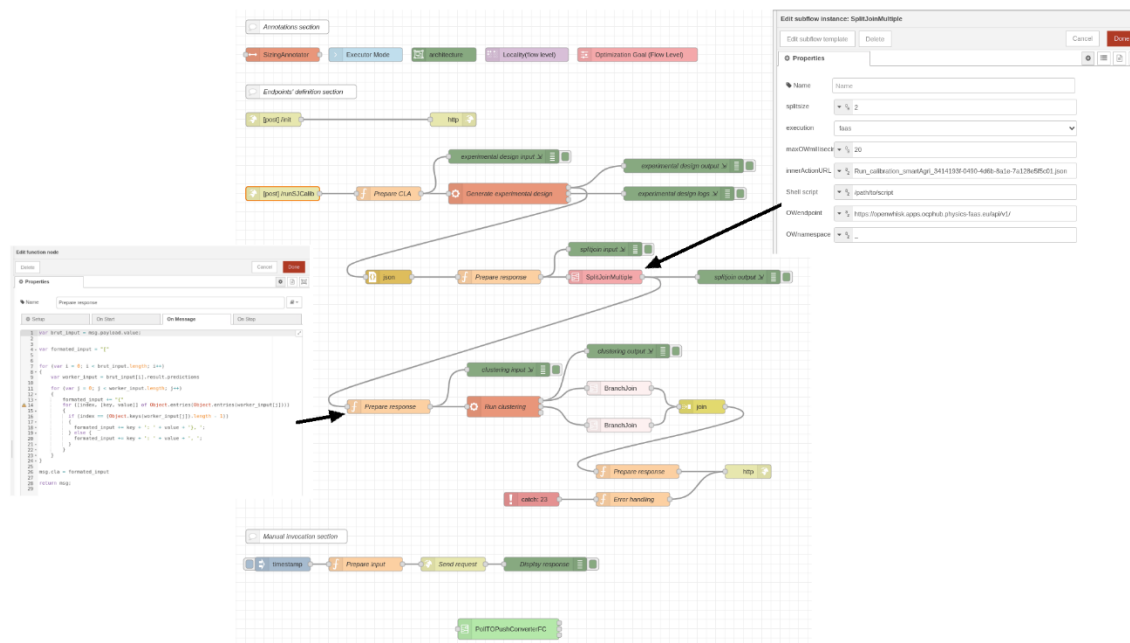


Figure 32: Calibration pipeline as a Node-RED flow using the split and join pattern for parallelization.

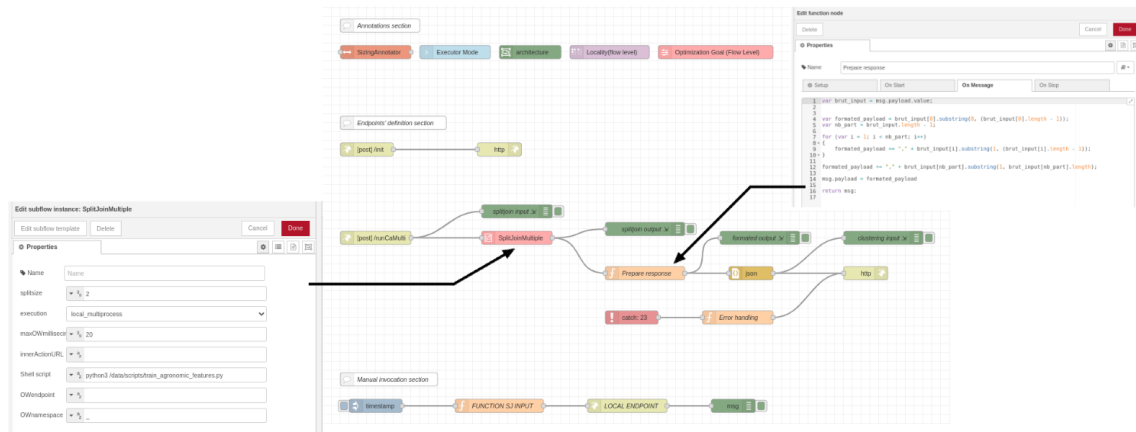


Figure 33: Node-RED flow allowing to run parameter set evaluation from an array of nodes such as generated by the Python script for experimental design generation with parallelization over processors.

4.3.3.2 Adaptation of legacy codes

To take advantage of FaaS the three steps of the calibration pipeline should be run separately. In this way each step could be run as a function with optimal placement according to resources needed and the simulations run during the calibration process could be parallelized using the split and join pattern. The legacy codes, consisting in one main script has then been split into three distinct scripts with ad-hoc I/O management and logging.

The script for experimental design generation has been implemented based on the legacy codes describing the calibration pipeline. It takes as input two lists, one describing the climate variables to use in the model and the other the way these variables are post-processed (Figure 34). The parameters to evaluate depend on the target agronomic variables, which are defined in the file referenced as AREA_FILE (read by the script for parameter set merit evaluation, Figure 35.A).

A. Main for Experimental design generation

```
if __name__ == "__main__":
    # Setup logging for writing in standard error
    logging.basicConfig(level=logging.INFO)

    # Collect input data from the command line arguments
    climate_variables = get_list_from_message(sys.argv[1])
    aggregator = get_list_from_message(sys.argv[2])

    # Generate experimental design
    experimental_design = generate_experimental_design(
        explored_variables=climate_variables,
        explored_values=aggregator,
    )

    # Format output
    sys.stdout.write(json.dumps(experimental_design))
```

B. Input formatting function

```
def get_list_from_message(config_str: str) -> List[str]:
    config_list = []

    if config_str is not None:
        config_str.replace(" ", "")
        config_list = config_str.split(",")

    return config_list
```

Figure 34: Adaptation of legacy codes for experimental design evaluation.

The script for parameter set merit evaluation integrates a main function which run the simulations with one or several parameters sets and perform the estimation its merit according to in situ measurements provided in the file referenced in the code as AREA_FILE (Figure 35.A). The parameter set list is built from the string provided as input using the prepare_input function (Figure 35.B).

A. Calibration main function

```
# PHYSICS main
if __name__ == "__main__":
    # Calibration context setup
    working_dir = "/usr/src/node-red"
    env = {
        "AREA_FILE": f"{working_dir}/input_data/agro_models_setup.geojson",
        "TARGET_CAMPAGNE": "2023",
        "MODEL_DIR": f"{working_dir}/input_data",
        "OUTPUT_DIR": f"{working_dir}/output_data",
        "CLIMATE_FILE_DIR": f"{working_dir}/input_data",
    }

    # Formatting string input
    parameter_sets = prepare_input(input_string=sys.argv)

    # Running parameters set evaluation
    sample_evaluation = main(env, experimental_design=parameter_sets)

    # Format output
    sys.stdout.write(json.dumps(sample_evaluation))
```

B. Parameter sets formatting

```
def prepare_input(input_string):
    ind = 1
    parameter_sets = []

    while ind < len(input_string):
        start_ind = 0
        if "(" in input_string[ind]:
            current_set = {}
            if "[" in input_string[ind]:
                start_ind = 2
            else:
                start_ind = 1

            current_key = input_string[ind][start_ind:(len(input_string[ind]) - 1)]
            ind += 1

            if ")" in input_string[ind]:
                current_val = input_string[ind][0:(len(input_string[ind]) - 2)]
                current_set[current_key] = current_val
                parameter_sets.append(current_set)
            else:
                current_val = input_string[ind][0:(len(input_string[ind]) - 1)]
                current_set[current_key] = current_val

            ind += 1

    return parameter_sets
```

Figure 35: Adaptation of legacy codes for parameter set merit evaluation.

The clustering of parameter sets according to their merit is a novel feature of the calibration pipeline implemented in PHYSICS. It allows to build a probability distribution for each target agronomic features, increasing the reliability and robustness of the method. The script integrates a function for building the dataset provided as input to the clustering algorithm from the output of SplitJoin node (Figure 36).

4.3.3.3 Pipeline deployment and testing

First, the calibration pipeline has been tested as a function to ensure that the I/O management between the different nodes of the pipeline is correct. Moreover, this flow will provide a baseline for performance evaluation.

Then we deploy (Figure 37.A) and test the parameter set evaluation flow both locally and using the Design Environment (Figure 37.B) to ensure that messages sent by the split and join node will be handled correctly.

Once the parameter set evaluation flow has been validated, the FaaS parallelized calibration pipeline has been tested. In real condition, this pipeline will be triggered by a Cybeletech engineer when needed and there is no gain in deploying it as a function. The testing has then been performed using the Node-RED panel of the Design Environment with parameter set evaluation being split and run as FaaS.

A. Dataset construction function

```
def build_dataset(input_string):
    ind = 1
    parameter_sets = []

    while ind < len(input_string):
        start_ind = 0
        if "(" in input_string[ind]:
            current_set = {}
            if "[" in input_string[ind]:
                start_ind = 2
            else:
                start_ind = 1

            current_key = input_string[ind][start_ind:(len(input_string[ind]) - 1)]
            ind += 1

            if ")" in input_string[ind]:
                current_val = input_string[ind][0:(len(input_string[ind]) - 2)]
                current_set[current_key] = current_val
                parameter_sets.append(current_set)
            else:
                current_val = input_string[ind][0:(len(input_string[ind]) - 1)]
                current_set[current_key] = current_val

            ind += 1

    param_dataset = pandas.DataFrame(parameter_sets)
    kmeans_dataset = pandas.DataFrame(param_dataset.loc[:, "score"], columns=["score"])

    return kmeans_dataset
```

B. Main function for Parameter set selection

```
def classify_parameters_set(
    kmeans_dataset: pandas.DataFrame,
    max_nb_clusters: int = 0,
    target_dist: float = 0.20,
) -> Tuple[pandas.DataFrame, pandas.DataFrame]: ...

def get_best_sets(
    group_merit: pandas.DataFrame,
    grouped_sets: pandas.DataFrame,
) -> List[Dict[str, str]]: ...

if __name__ == "__main__":
    # Setup logging for writing in standard error
    logging.basicConfig(level=logging.INFO)

    # Building dataset from output of SplitJoin calibration
    parameter_set_merit = build_dataset(sys.argv)

    # Clustering of parameter sets
    logging.info("Clustering parameter sets...")
    centroids, kmeans_labels = classify_parameters_set(parameter_set_merit)
    logging.info(f"({len(centroids)}) clusters have been generated.")

    # Extracting best parameters sets
    logging.info("Collecting best parameter sets...")
    best_parameter_sets = get_best_sets(centroids, kmeans_labels)
    logging.info(f"({len(best_parameter_sets)}) have been retained.")

    # Format output
    sys.stdout.write(json.dumps(best_parameter_sets))
```

Figure 36: Adaptation of legacy codes for parameter set selection.

In the running example depicted in Figure 38, a parameter set grid including 27 nodes is generated by the Generate experimental design node (Figure 39). The string returned by this node is parsed in order to create an array of parameter sets which is sent to the SplitJoinMultiple node. The nodes are divided into three

groups and three functions are invoked as FaaS, each processing one of the groups (Figure 40). The three evaluations outputted by the SplitJoinMultiple node are aggregated in a single string which is sent to the Run clustering node. The parameter sets are sorted according to their score and the best parameters sets are returned (Figure 41).

The same experiment has been conducted for the multiprocessing version of the parameter set evaluation with deployment and testing of the multiprocessed flow.

4.3.4 Concluding remarks

The source material for the prototype as described here can be found on the PHYSICS project internal Git repository, here:

https://repo.apps.ocphub.physics-faas.eu/PHYSICS/test/src/smart_agriculture/

Access to this repository is limited to members of the PHYSICS Consortium but may be granted upon request.

A. Deployment of the parameter set evaluation function

Run_calibration e67808ceeb3bc29a ✓				
Document ID	URL	Action name	Built date	
6528f9f775813f77b56edb4b	registry.apps.ocphub.physics-faas.eu/custom/smartAgri:10	Run_calibration_smartAgri_aaa43779-0178-41bf-994a-bcdd877681fc.json	10/13/23, 10:04 AM	
65290a9b75813f77b56edb4d	registry.apps.ocphub.physics-faas.eu/custom/smartAgri:12	Run_calibration_smartAgri_08a9858e-b12d-4633-927a-52262ada6757.json	10/13/23, 11:15 AM	
6537d98ee44cd8c531da1615	registry.apps.ocphub.physics-faas.eu/custom/smartAgri:36	Run_calibration_smartAgri_fb49244f-6065-4639-b3cc-647d4c4aee5a.json	10/24/23, 4:49 PM	
6538dd54e44cd8c531da1617	registry.apps.ocphub.physics-faas.eu/custom/smartAgri:38	Run_calibration_smartAgri_3414193f-0490-4d6b-8a1e-7a128e5f5c01.json	10/25/23, 11:18 AM	
653908c5e44cd8c531da161b	registry.apps.ocphub.physics-faas.eu/custom/smartAgri:41	Run_calibration_smartAgri_e4a3d7f0-bd0c-4fbl-be0a-c539faf4a8aa.json	10/25/23, 2:23 PM	

Rebuild

B. Testing of the parameter set evaluation function

Run_calibration_smartAgri_e4a3d7f0-bd0c-4fbl-be0a-c539faf4a8aa.json 3f48143b052c463388143b052cc63392

Params

[Object Object],[Object Object]

Result

```

[
  {
    "TM": "sum",
    "net_radiation": "sum",
    "prec": "sum",
    "score": 1.3901060030534906
  },
  {
    "TM": "sum",
    "net_radiation": "min",
    "prec": "sum",
    "score": 0.3045419990518521
  }
]

```

```

{
  "input": [
    {
      "TM": "sum",
      "prec": "sum",
      "net_radiation": "sum"
    },
    {
      "TM": "sum",
      "prec": "sum",
      "net_radiation": "min"
    }
  ]
}

```

Figure 37: Parameter set evaluation flow deployment (A) and testing (B) using the Design Environment.

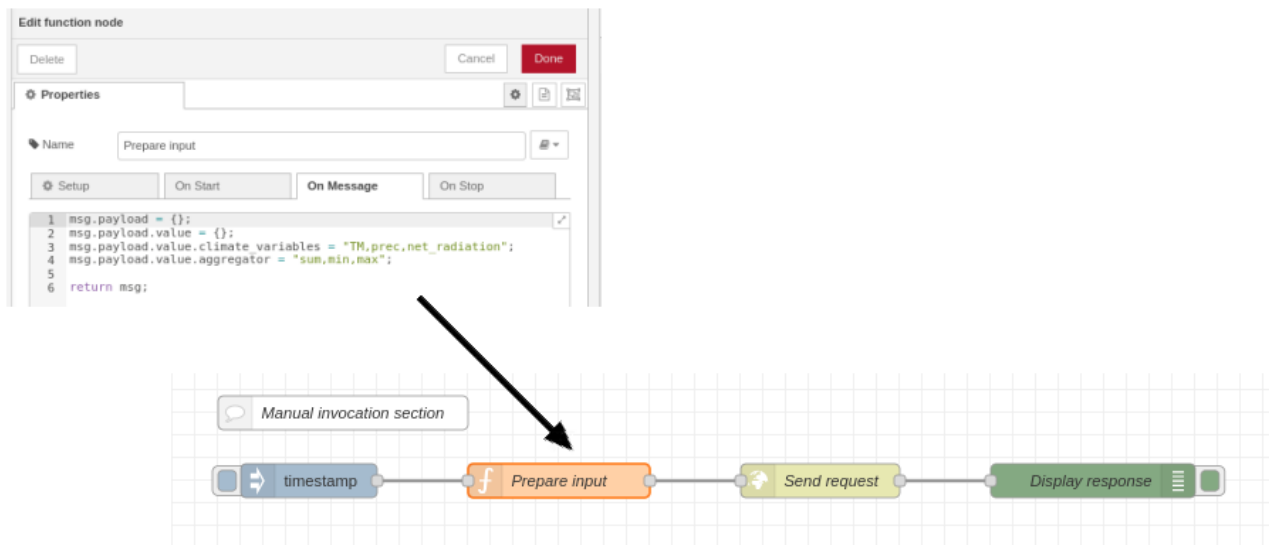


Figure 38: Flow for local invocation of the split and join calibration pipeline.

Input for parameter sets generation

```

21/11/2023 11:57:58 node: experimental design input
msg.payload: Object
  ▾ object
    ▾ value: object
      climate_variables: "TM,prec,net_radiation"
      aggregator: "sum,min,max"

```

Output of experimental design node

```

21/11/2023 11:57:58 node: experimental design output
msg.payload: string[1458]
[{"TM": "sum", "prec": "sum", "net_radiation": "sum"},
{"TM": "sum", "prec": "sum", "net_radiation": "min"},
{"TM": "sum", "prec": "sum", "net_radiation": "max"},
{"TM": "sum", "prec": "min", "net_radiation": "sum"},
{"TM": "sum", "prec": "min", "net_radiation": "min"},
{"TM": "sum", "prec": "min", "net_radiation": "max"},
{"TM": "sum", "prec": "max", "net_radiation": "sum"},
{"TM": "sum", "prec": "max", "net_radiation": "min"},
{"TM": "sum", "prec": "max", "net_radiation": "max"},
{"TM": "min", "prec": "sum", "net_radiation": "sum"},
{"TM": "min", "prec": "sum", "net_radiation": "min"},
{"TM": "min", "prec": "sum", "net_radiation": "max"},
{"TM": "min", "prec": "min", "net_radiation": "sum"},
{"TM": "min", "prec": "min", "net_radiation": "min"},
{"TM": "min", "prec": "min", "net_radiation": "max"},
{"TM": "min", "prec": "max", "net_radiation": "sum"},
{"TM": "min", "prec": "max", "net_radiation": "min"},
{"TM": "min", "prec": "max", "net_radiation": "max"},
{"TM": "max", "prec": "sum", "net_radiation": "sum"},
{"TM": "max", "prec": "sum", "net_radiation": "min"},
{"TM": "max", "prec": "sum", "net_radiation": "max"},
{"TM": "max", "prec": "min", "net_radiation": "sum"},
{"TM": "max", "prec": "min", "net_radiation": "min"},
{"TM": "max", "prec": "min", "net_radiation": "max"},
{"TM": "max", "prec": "max", "net_radiation": "sum"},
{"TM": "max", "prec": "max", "net_radiation": "min"},
{"TM": "max", "prec": "max", "net_radiation": "max"}]

```

Logs of experimental design node

```

21/11/2023 11:57:58 node: experimental design logs
msg.payload: string[74]
  ▾ string[74]
    INFO:root:Generating parameter sets...
    INFO:root:27 have been generated.

```

Figure 39: Input, output and logs of the Generate experimental design node for the running example.

After having described the first version of the “smart agriculture Prototype”, we now look back at the initial functional specifications that were defined in section 3.3. For each of the Functional Specifications, we discuss if and how the specifications are fulfilled, and – in case of a partial fulfillment – the work that remains to be done in the next iteration(s) of the prototype. The fulfillment of the functional specifications introduced in Table 3 is discussed in Table 6.

Table 6: Fulfillment of the Functional requirements for the Smart Agriculture use case.

Code	Functional Requirements
FRS-UC3-01	Fulfilled. A first script for data collection has been integrated in the Node-RED ETL flow.
FRS-UC3-02	Fulfilled. The pipeline runs if the docker is up with a user-defined time step and is resilient to connection failure.
FRS-UC3-03	Fulfilled. A first deployment has been performed on Cybeletech by using the PHYSICS Design Environment. Moreover, the image built during the deployment phase has been pull and used to deploy the data collection pipeline.
FRS-UC3-04	Fulfilled. The simulation and calibration pipelines can be invoked using the test panel of the Design Environment or the endpoint exposed by the Node-Red flow.
FRS-UC3-05	Fulfilled. The simulation and calibration pipelines have been deployed as FaaS using the DE and benefits from annotations and patterns developed in PHYSICS.
FRS-UC3-06	Fulfilled. The split and join pattern has been integrated in the calibration flow in order to parallelized the runs, allowing to reduce the runtime.

In the smart Agriculture Use Case, three applications have been adapted and tested using the components developed in PHYSICS. The data collection pipeline, adapted during the first period, takes advantage of the Edge-ETL pattern to increase the reliability of the process and reduce the adaptation time from one greenhouse to another. The deployment on the edge is facilitated by the Design Environment interface which allows to build and retrieve an image embedding all the required components. The simulation pipeline has been adapted so that it can be easily deployed and run as FaaS, significantly reducing the infrastructure costs. Finally, the calibration pipeline has been adapted to integrate the split and join pattern, which enables high level of parallelization using the FaaS paradigm. These two last applications have been successfully deployed in the cloud and tested using the Design Environment.



Figure 40: Output of the Generate experimental design node formatted for the SplitJoinMultiple node and output of each worker. In this context a worker is an instance of the parameter set evaluation function deployed and invoked as FaaS.

Brut SplitJoinMultiple output

```

21/11/2023 12:01:21 node: splitjoin output
msg.payload: Object
  object
  value: array[3]
    0: object
      result: object
        predictions: array[9]
          0: object
            TM: "sum"
            net_radiation: "sum"
            prec: "sum"
            score: 1.3901060030534906
          1: object
            TM: "sum"
            net_radiation: "min"
            prec: "sum"
            score: 0.3045419990518521
          2: object
          3: object
          4: object
          5: object
          6: object
          7: object
          8: object
        size: 694
        status: "success"
        success: true
    1: object
      result: object
        predictions: array[9]
          0: object
            TM: "min"
            net_radiation: "sum"
            prec: "sum"
            score: 1.652814268338113
          1: object
            TM: "min"
            net_radiation: "min"
            prec: "sum"
            score: 0.6921545619407781
          2: object
          3: object
          4: object
          5: object
          6: object
          7: object
          8: object
        size: 689
        status: "success"
        success: true
    2: object
      result: object
        predictions: array[9]
          0: object
            TM: "max"
            net_radiation: "sum"
            prec: "sum"
            score: 1.3957930149248599
          1: object
            TM: "max"
            net_radiation: "min"
            prec: "sum"
            score: 0.747686550581754
          2: object
          3: object
          4: object
          5: object
          6: object
          7: object
          8: object
        size: 690
        status: "success"
        success: true

```

SplitjoinMultiple output formatted for clustering

```

21/11/2023 12:01:21 node: clustering input
msg.cla: string[1061]
"([TM: sum, net_radiation: sum, prec: sum, score: 1.3901060030534906),
(TM: sum, net_radiation: min, prec: sum, score: 0.3045419990518521)},
(TM: sum, net_radiation: max, prec: sum, score: 0.29954778629887885)},
(TM: sum, net_radiation: sum, prec: min, score: 2.043490818760501)},
(TM: sum, net_radiation: min, prec: min, score: 0.48930878505632214)},
(TM: sum, net_radiation: max, prec: min, score: 0.8846742372158805)},
(TM: sum, net_radiation: sum, prec: max, score: 1.3379308314525164)},
(TM: sum, net_radiation: min, prec: max, score: 0.42493902778756537)},
(TM: sum, net_radiation: max, prec: max, score: 0.7996803160129049)},
(TM: min, net_radiation: sum, prec: sum, score: 1.652814268338113)},
(TM: min, net_radiation: min, prec: sum, score: 0.6921545619407781)},
(TM: min, net_radiation: max, prec: sum, score: 0.8566379863776183)},
(TM: min, net_radiation: sum, prec: min, score: 1.7549554507525567)},
(TM: min, net_radiation: min, prec: min, score: 0.8512159708963796)},
(TM: min, net_radiation: max, pr..."

```

Output of clustering node

```

21/11/2023 12:01:22 node: clustering output
msg.payload: string[343]
"([TM: "sum", "net_radiation": "min", "prec": "sum", "score": "0.3045419990518521"},
(TM: "sum", "net_radiation": "max", "prec": "sum", "score": "0.29954778629887885"},
(TM: "sum", "net_radiation": "min", "prec": "min", "score": "0.48930878505632214"},
(TM: "sum", "net_radiation": "min", "prec": "max", "score": "0.42493902778756537"}])"

```

Logs of clustering node

```

21/11/2023 12:01:22 node: clustering logs
msg.payload: string[975]
string[975]
INFO:root:Building dataset for clustering...
INFO:root:...Done. (27, 7)
INFO:root:Clustering parameter sets...
INFO:root:6 clusters have been generated.
INFO:root:Collecting best parameter sets...
INFO:root:4 have been retained.
INFO:root:[{"TM": "sum", "net_radiation": "min", "prec": "sum", "score": "0.3045419990518521"},
{"TM": "sum", "net_radiation": "max", "prec": "sum", "score": "0.29954778629887885"},
{"TM": "sum", "net_radiation": "min", "prec": "min", "score": "0.48930878505632214"},
{"TM": "sum", "net_radiation": "min", "prec": "max", "score": "0.42493902778756537"}]

```

Figure 41: Raw output of the SplitJoinMultiple node and formatted string used as input of the Run clustering node, output of the clustering and corresponding logs.

5 CONCLUSIONS

This document accompanies the delivery of the very first three demonstrators that have been developed to run on top of the PHYSICS Platform. The Smart Manufacturing use case demonstrates a quality control scenario, the eHealth use case demonstrates three scenarios (inference, phenotyping and synthesis), while the Smart Agriculture use case focuses on data collection pipelines, all using Node-RED flows to model these processes as a series of functions. These demonstrators are the final work of experimenting with the different use cases in a “FaaSified” manner using the PHYSICS Platform.

This deliverable describes the adaptation of the application components in the PHYSICS environment, the functional requirements per each use case and the usage of the PHYSICS tools. The prototypes are documented using the design environment of PHYSICS and they all represent different utilization of the developed PHYSICS components.

All three use cases have finalized their experimentation activities, meaning that the flows have been created for all their scenarios, and they have been tested locally. Services have been deployed from these flows, and the services have also been tested. The outcome of the experimentation (and thus of Task 6.3, Use Cases Adaptation and Experimentation) is a total of 8 scenario services across the 3 use cases, all of them ready for evaluation in the context of Task 6.4, Use Cases Evaluation).

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