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SESAME

D1.7 : Validation Strategy

This deliverable includes validation strategy, validation objectives, validation scenarios, validation plan.

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22/04/2020	V1	AGS	First issue
27/04/2020	V2	AGS	Validation scenarios added
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12/06/2020	V4	Predict & Eurecat	Inputs for validation methodology

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01 / Introduction

02 / Validation objectives

03 / Validation scenarios

04 / Validation plan

01 / Introduction

Introduction

This deliverable describes how is measure the success of SESAME project.

The SESAME project aims to harness digital technologies, processes and methods for automation of the European launchers' manufacturing and operations by :

(a) develop new Predictive Maintenance and Quality components to implement new automated launcher production and operations maintaining quality and reliability,

(b) implement new logistic processes that allows an optimal management of resources in an environment where resources are shared among different organisations and products,

(c) accompany the consequent transformation of human competencies, and to create competency framework for newly established positions.

The usefulness of the SESAME results will be validated in a series of Use Cases deployed at the premises of the SESAME end user partners and operated with real technical data. Such demonstrators will be representative of the functional needs of the use case and will reach TRL 5 to TRL 7.

Grant agreement extract

Task 1.5: Validation Strategy and Performance Framework (AGS, CNES, NUPSPA).

Input: Baseline data base (WP1.1), End User Needs for Analytics (WP1.3).

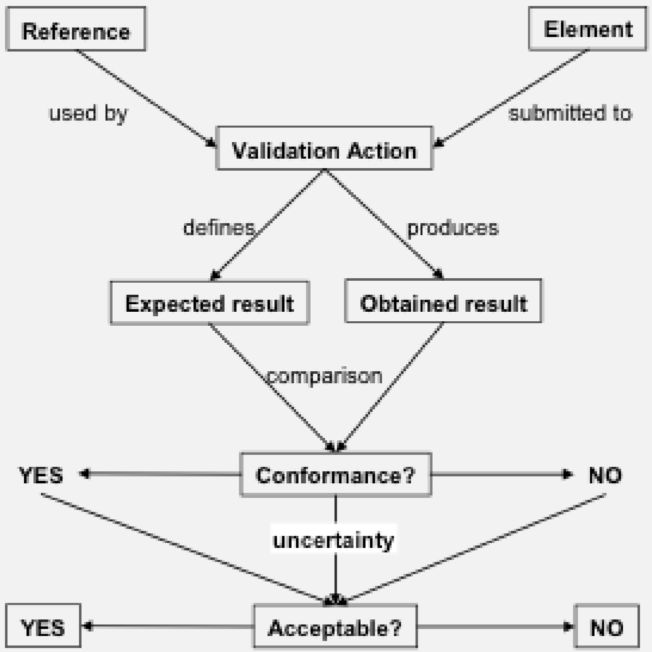
This task defines the operational validation strategy by defining a performance framework, performance objectives, and the modality of the measurement (how performance are measured, when and by whom). The validation plan shall allow evaluating impact on operational key performance indicators, impact on safety and of human factors, usability by the staff, ethics. Measurement shall be undertaken all along the project and permit in WP 7 to calculate the return of investment, risks and opportunities for the deployment phase. The validation strategy includes the process, methods and tools and the digital platform.

Output: Deliverable 1.7 Validation Strategy.

Validation Logic

Validation is the confirmation, through the provision of objective evidence, that the requirements for a specific intended use or application have been fulfilled. With a note added in ISO 9000:2005: validation is the set of activities that ensure and provide confidence that a system is able to accomplish its intended use, goals, and objectives in the intended operational environment.

The purpose of validation, as a generic action, is to establish the compliance of any activity output as compared to inputs of the activity. It is used to provide information and evidence that the transformation of inputs produced the expected and right result. Validation is based on tangible evidence; i.e., it is based on information whose veracity can be demonstrated by factual results obtained from techniques or methods such as inspection, measurement, test, analysis, calculation, etc. Thus, to validate a system (product, service, or enterprise) consists of demonstrating that it satisfies its system requirements and eventually the stakeholder's requirements depending on contractual practices. From a global standpoint, the purpose of validating a system is to acquire confidence in the system's ability to achieve its intended mission, or use, under specific operational conditions.



02 / Validation Objectives

High level objectives

The following section will display the high level objectives of the project. Each high level objective has been declined in several sub-objectives, which are related to a success criteria.

This sections also aims to present the Key Performance Indicators (KPI). Each KPI refers to a high level objective.
The selected KPIs will allow the evaluation of the project's success.

High level objectives 1/2

Objective		Sub-objective		Success criteria	Associated activities
SES_OBJ_1	Predict the quality of the welds and the maintenance of the Friction Stir Welding machine.	SES_OBJ_1.1	Collect and share quality and maintenance data coming from the FSW machine.	Data received by the concerned partners.	Validate exportable data with DGA and Export Control authorities.
		SES_OBJ_1.2	Deploy a collaborative data science plateform shared among all the partners.	Data plateform accessible from each partner.	Build a collaborative cloud environment accessible from each partner
		SES_OBJ_1.3	Develop and implement new algorithms into an automated launcher production environment.	Predictive patterns for machine failures and welding anomalies.	Algorithms trained and validated.
SES_OBJ_2	Implement new logistic processes and optimize supply chain assets within the Guyana Space Center.	SES_OBJ_2.1	Gather and share geolocation and sheduling data from CSG's shared assets.	Data received by the concerned partners.	Validate exportable data with DGA and Export Control authorities. Trackers deployment.
		SES_OBJ_2.2	Deploy a collaborative data science plateform shared among all the partners.	Data plateform accessible from each partner.	Build a collaborative cloud environment accessible from each partner
		SES_OBJ_2.3	Develop and implement new algorithms to optimize supply chain assets and logistic operations agility	Dynamic assets' pools reconfiguration scenarios proposed.	Algorithms trained and validated.

High level objectives 2/2

Objective		Sub-objective		Success criteria	Associated activities
SES_OBJ_3	Accompagny the transformation of human competencies and jobs.	SES_OBJ_3.1	Educate employees to the data science.	Employees certified by Dataiku.	Follow Dataiku courses. Documentation review. Coding workshops. Data governance workshops.
		SES_OBJ_3.2	Measuring the Technology Readiness and Attitude Towards Automation in the pre-work, pre-operational phase	Amount of questionnaires collected	Adapting the research tools Conducting the research Collecting the responses Analysing the responses Drafting the report
		SES_OBJ_3.3	Measuring work engagement, trust in automation and job-related aaffective wellbeing , operational phase	Amount of questionnaires collected	Adapting the research tools Conducting the research Collecting the responses Analysing the responses Drafting the report
		SES_OBJ_3.4.	Conducting interviews with staff to discover critical competencies	Number and depth of interviews	Developing of research tools Conducting the interviews Analysing the verbatim transcripts Drafting the updated competency matrix

Key Performance Indicators

Usecase 1 – Predictive maintenance

The following section will display each Key Performance Indicator for the Predictive Quality part of the 1st usecase.

Key Performance Indicators 1/5

KPI		Related objective	Goal	Calculation	Unit
SES_KPI_1	Amount of data exported	SES_OBJ_1	Assess the amount of data needed.	∑ of all the data files shared	Mo
SES_KPI_2	Predictive quality algorithm maturity.		Assess the evolution of the preditcitve quality algorithm training.	Algorithm result/Real result	%
SES_KPI_3	Early detection of faults and failures		Difference between predictive maintenance and conditional maintenance	Time difference between algorithm detection and detection without algorithm	Hours
SES_KPI_4	User needs matrix coverage		Asses the coverage of the user needs	Yes/Partially/no	/

Key Performance Indicators 2/5

KPI		Related objective	Goal	Calculation	Unit
SES_KPI_5	Early detection of faults and failures	SES_OBJ_1	Difference between predictive maintenance and conditional maitnance	Time difference between algorithm detection and detection without algorithm	Hours
SES_KPI_6	Total maintenance costs		Assess the evolution of maintenance costs, detailed p.31	∑ costs detailed in p.31	€
SES_KPI_7	Current Amount of variables used / Total Amount of variables		Assess the amount of pertinent data to be used.	∑ used variables	€
SES_KPI_8	Non quality costs		Assess the evolution of quality costs, detailed p.32	∑ costs detailed in p.32	€

Key Performance Indicators 3/6

KPI		Related objective	Goal	Calculation	Unit
SES_KPI_9	Prediction time performance	SES_OBJ_1	Incoming data is processed, offering predictions within cycle time.	Time_received_data – Time_prediction	seconds
SES_KPI_10	Non-quality prediction accuracy		Identify quality deviations in the tank welding	Accuracy (ACC) = (Σ True positive + Σ True negative)/Σ Total population	%
SES_KPI_11	Prediction confidence interval		Provide prediction confidence intervals for helping the human expert to assess welding quality	Probability of the prediction	%
SES_KPI_12	Data incoherency detection and alarm		Automatically detects data incoherencies raising alarms and warnings.	There is no a clear mesure, most similar should be: Accuracy (ACC) = (Σ True positive + Σ True negative)/Σ Total population	%

Key Performance Indicators 4/6

KPI		Related objective	Goal	Calculation	Unit
SES_KPI_13	Outlayer detection warning	SES_OBJ_1	Human-AI collaboration: Prompt detection outlayers helps to improve data labelling and thus predictive quality performance.	Accuracy (ACC) = (Σ True positive + Σ True negative)/Σ Total population	%
SES_KPI_14	Quality alarm generation.		- Scrap reduction. - Energy consumption - Raw material consumption - Reduced reworks - Reduced production time	Forecasting of > 10 samples	N.A.
SES_KPI_15	Input data Flexibility		Dynamic process monitoring, new trends in process monitoring	1 new sensor	N.A.

Key Performance Indicators

Usecase 1 – Predictive maintenance

The following section will display each Key Performance Indicator related to the SES_OBJ_2 objective

Key Performance Indicators 3/5

KPI		Related objective	Goal	Calculation	Unit
SES_KPI_5	Amount of data exported to the partners.	SES_OBJ_2	Assess the amount of data needed.	∑ of all the data files shared	Mo
SES_KPI_6	Amount of assets optimized		Assess the evolution of optimized assets	$NbAsset_{t0} - NbAsset_{t}$	N.A.
SES_KPI_7	Assets cost evolution		Assess the evolution of the costs related to the assets.	$CostAsset_{t0} - CostAsset_{t}$	€
SES_KPI_8	Asset usage		Assess the evolution of a better usage of assets on the	Utilisation time/Site opening time	%

Key Performance Indicators

Usecase 1 – Predictive maintenance

The following section will display each Key Performance Indicator related to the SES_OBJ_3 objective.

Key Performance Indicators 4/5

KPI		Related objective	Goal	Calculation	Unit
SES_KPI_9	Amount of colleagues certified by Dataiku	SES_OBJ_3	Assess the evolution of colleagues sensibilized to data science.	∑ of all the colleagues certified	People/month
SES_KPI_10	Amount of usecases implemented into Dataiku		Assess the evolution of work transplanted within the data plateform	∑ of all the usecases implemented within Dataiku	Usecases/month
SES_KPI_11	Knowledge Dissemination		Maximize the number of viewer of the web site.	∑ of view	Views/month
SES_KPI_12	External communication		Web site is online.	% of online time / downtime	%

Key Performance Indicators 5/5

KPI		Related objective	Goal	Calculation	Unit
SES_KPI_13	Amount of questionnaires collected in pre-operational phase	SES_OBJ_3	Assess the level of technology readiness and attitudes towards automation	∑ of collected questionnaires	%
SES_KPI_14	Amount of questionnaires collected in operational phase		Assess the level of work engagement, trust in automation and affective wellbeing	∑ of collected questionnaires	%
SES_KPI_15	Identified critical competencies		Establish a competency framework matrix	∑ of relevant themes	No of themes

03 / Validation scenarios

Validation scenarios

The following section will display the different scenarios that will allow to validate each kind of algorithm.

Each validation grid which will allow the validation of algorithms developed for each objective. A grid shows up the different kind of validation scenarios.

The main categories of complexity factors are sub-divided in more detailed ones. The description and definition of each of the sub-divided factors is provided in the table below each validation grid.

Validation scenarios

Usecase 1 – Predictive quality

For defining the validation strategy of the predictive quality module, a scaling approach is conceptualized by defining simpler scenarios and boundary conditions at first and then scaling up to production conditions.

Several technics and methodologies can be implemented in order to validate the models performance. Within SESAME predictive quality solution, cross validation methodologies will be used to benchmark model performance. Cross validation techniques are useful to set the right methodology for evaluating the performance of the different machine learning solutions or algorithms in a process/project agnostic manner.

- Cross-validation methods will be implemented to test the performance of several algorithmic approaches. Cross-validation is a resampling procedure that helps to evaluate machine learning and AI models on a limited dataset.
  - One of the most used methodologies in cross-validation is the k-fold, which consists in partitioning the available data into k different subsets and training the selected algorithm with each partition to obtain a strong estimation of the algorithm performance and its dispersion.
  - If the data is limited, Leave One Out Cross Validation (LOOCV) takes K = 1, and thus each data sample is used in the test set. This approach helps when the data samples are reduced and thus participates both in the training and the testing set.
  - In Stratified Cross Validation the splitting of data into folds may be governed by a criterion that ensures each fold has the same proportion of observations of every class. This strategy helps in unbalanced datasets, because guarantees that all classes (qualities) participate both in the training and the test sets.

Nevertheless, project or process specific considerations need to be taken into account to address the process challenges and ensure a tailored solution. In the frame of SESAME project, predictive quality module focuses on the FSW stations of the LLPM assembly:

- Longitudinal station
- Circular station

Validation scenarios

Usecase 1 – Predictive quality

For each station, a similar validation strategy will be designed:

- The first step of Predictive Quality model validation will be based on a detailed Design of Experiment (DoE) where a very controlled dataset is acquired and analyzed. This dataset will be created specifically for targeting the quality characteristics to be monitored. Different cross-validation techniques will be implemented to evaluate the performance metrics of the different algorithms. This dataset should be completely labeled (human supervision) In order to ensure a proper model training and testing. This firs step will provide the foundations to establish the correlations between measured parameters and quality outputs of both welding stations.
- The second step will focus on testing the selected models trained using the first step datasets (DoE) with new tests and validate the response of the predictive quality models. These validations will involve human supervision and target as much samples as possible. This step will focus as well on the study of model robustness and generalization, evaluating how different welding runs (and tanks) can be modelled together.
- In the last step, human supervision of the Predictive Quality model results is only performed under demand in case of low prediction confidence. This approach will also help to increase the labeled datasets and thus enhance future training steps. A trained model will be deployed to monitor welding quality for both longitudinal and circular station and cross-checking with NDI quality assessment will be performed.

Relevant production KPIs for the predictive quality models based on end-users needs for the longitudinal and circular stations are described in page 15 and page 16.

Validation methodology

Usecase 1 – Predictive maintenance

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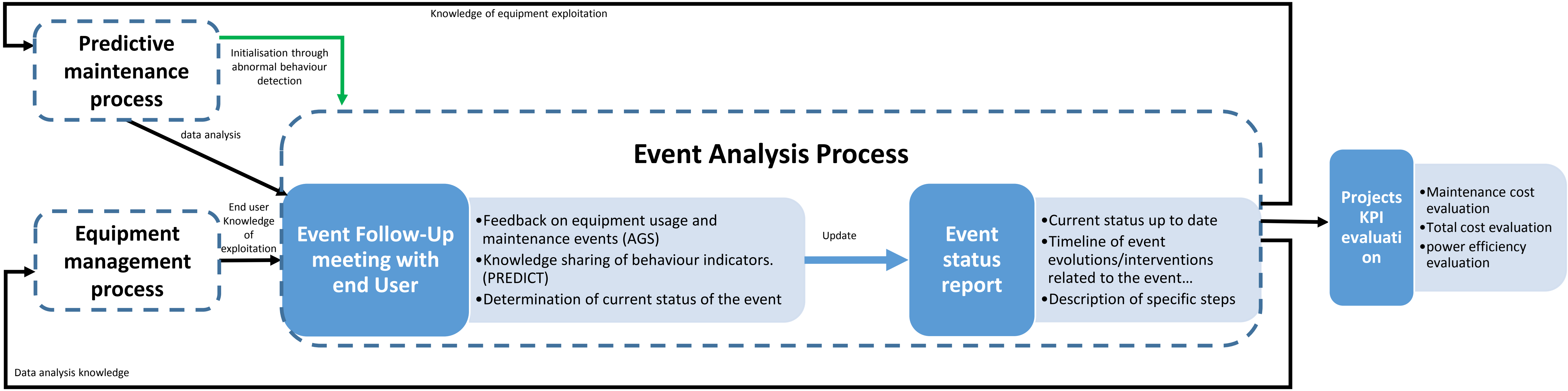
PREDICT

Each abnormal behaviour detected using predictive maintenance tools will trigger an **event analysis process**. The end user and Predict will work in conjunction to determine the **event analysis status** among standardized terms to follow the event resolution until it is either finalized (no more input to add to this event) or dismissed (Detection is considered not relevant).
The **event analysis process** is expected to have an impact on **equipment management process** as the knowledge of current health status and detections may trigger interventions on the equipment.
An **event status report** will be generated and updated during the whole process for each event. The reports will then be used to **evaluate the different KPIs of the project** through the aggregation of the feedbacks of the events evaluated.



Validation scenarios

Usecase 2 – Supply chain asset optimization

Complexity factors	S1_Easy	S2_Easy	S3_Medium	S4_Medium	S5_Medium	S6_Hard	S7_Hard
Social factors							
Strike				x		x	
Trackers sabotage			x				x
Weather conditions							
Storm			x		x	x	
Bad visibility				x			x
Equipment factors							
Asset malfunction	x					x	
Too frequent usage		x			x		x
Ground operations							
Road destruction			x		x	x	
Electrical failure				x			x

Validation scenarios

Usecase 2 – Supply chain asset optimization

Complexity factors description	
Social factors	
Strike	Strike implies that only a part of the staff, that can be variable, will be available to work on site.
Trackers sabotage	Trackers sabotage implies that someone, or somthing detroyed/removed to tracker from the original asset it was sticked on.
Weather conditions	
Storm	Storm implies strong winds, lightning strikes, and heavy rain. It adds complexity and worload within supply chain operations.
Bad visibility	Bad visibilty introduce non-routine situations, drivers will have to drive slowly, and assets will be hard to localize and indentify visually, which adds complexity and workload.
Equipment factors	
Asset malfunction	Malfunctions introduce non-routine situations and require the use of standby equipment and procedures.
Too frequent usage	High utilization frequency means that the asset is being used >70% of the time.
Ground operations	
Road destruction	Road destruction translated the fact that an intinerary isn't available anymore.
Electrical failure	Electrical failure implies that a part (or the entirety) of the CSG isn't alimented in electricity anymore.

04 / Validation plan

Return On Investment axis 1/2

Predictive maintenance

General costs:

- Spare parts reduction (e.g. welding heads ccosts 100k€/year yet, 70% reduction expected) ,
- NTI5 costs reduction (outside of maintenance contract costs),
- Reduction of regulatory costs (specific controls on the machine),
- Avoidance of systemic maintenance,
- Avoidance of non quality exported,
- Avoidance of breakdowns,
- Energy consomption optimization,

Predictive quality

General costs:

- Control time reduction, thus stock & WIP reduction,

Return On Investment axis 2/2

New logistic processes and asset tracking

Asset fleets optimization – 20% of asset fleet reduction, rental contracts reduced, reinvestment reduced, maitnenance costs reduced

Energy consumption – less energy spend in both fuel and electricity

Stock & WIP reduction – Stock & WIP reduction thanks to planning optimization

Time spent searching assets – less time spent searching for assets on site (2h per month per dedicated person).

Ethics

- The main ethical issue relevant for project SESAME is that the way in which Big Data techniques operate, by means of inferences, raises uncertainties in terms of the reliability of the results (the human bias can occur at several levels: in the selection of the dataset for SESAME open data platform (WP2), in the design of the architecture specification), or of the transparency/opacity of the decision-making process related with metadata management and data governance (WP2 and WP4).
- Aware of the potential ethical issues of the use of the Big Data (WP2 and WP4), SESAME proceeds carefully in the development of the platforms. Two main safeguards are built in the project:
  - A detailed Ethical Risk Assessment is carried out throughout the project, involving technical partners and end users in the design of SESAME platform and solutions and the related methodologies (WP6, T6.2: *Ethics Guidelines for development and use of SESAME tools and methodologies, M33*). Health and Safety issues and environmental impact will be considered. This task will provide input to WP4, WP5 and remains active during development and testing of the tools. The task also establishes ethics and compliance guidelines for professionals working with the tools and solutions developed by the project. These Guidelines are aimed at both technology developers and End Users.
  - A task that provides the definition of the specifications for the functional requirements of the Big Data management infrastructure for inclusion in the global architecture of the project, including authorization among other features (WP2, T2.3 Prototype 2: Platform Administration, Cybersecurity, Data Information Lifecycle).

END OF DOCUMENT

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