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(Grant Agreement No 723145)

D8.6 Value Chain Pilot II

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Dimitris Gkortzis (ELDIA)	2019-08-26	Approved for submission

Index:

1 Executive Summary

This document is one of the deliverables of the COMPOSITION project, reporting the activity developed under the scope of WP8, namely in Task 8.2 “Intrafactory Value Chain Centric Pilot”.

This report describes how the COMPOSITION operating system can be implemented in a value chain centric pilot, showing modularity, scalability and re-configurability of the platform across multiple application domains. These characteristics will be demonstrated in this deliverable with the use of the same adaptable solutions in two unlike manufacturing industries: medical devices and lifts.

This document presents the use cases developed at Boston Scientific Ltd and KLEEMANN and shows they are successfully implemented. Five intra factory use cases where implemented; three at Boston Scientific and two at KLEEMANN

- UC-BSL-2 Predictive Maintenance
- UC-BSL-3 Asset Tracking
- UC-BSL-5 Equipment Monitoring and Line Visualisation
- UC-KLE-1 Maintenance Decision Support
- UC-KLE-3 Scrap Metal and Recyclable Waste Transportation

Data is being collected and transmitted real time to the cloud-based COMPOSITION BMS and being used as learning tool for the artificial neural networks that will predict the failure probabilities of a specific equipment.

Several KPI’s were identified and they are displayed using an HMI specifically designed for the COMPOSITION project. A first evaluation of that interface already took place and its discoveries used to generate the HMI’s next iteration.

In Boston Scientific, UC-BSL-2 Predictive Maintenance gave promising results, meeting or exceeding the targets on the relevant KPIs. UC-BSL-3 Asset Tracking showed great improvements in terms of cost savings and reduction in lost time looking for equipment. Although UC-BSL-5 Equipment Monitoring and Line Visualisation was not running long enough to show significant results for some of the KPIs, with full line visualisation, there will be an overall reduction in down-time.

At KLEEMANN, UC-KLE-1 Maintenance Decision Support met most of its targets, with cost savings for process monitoring and a reduction in down-time. For UC-KLE-3 Scrap Metal and Recyclable Waste Transportation, the forklift’s fuel consumption and cost were reduced by 4%, with further improvement expected if the system is expanded in the future.

Eventual risk probabilities from this pilot can be easily managed and prevented and both use cases and technology are well accepted and already showing how they will beneficially impact the industry, making the pilot partners already envision future follow ups for this project that can take advantage of the COMPOSITION platform, such as large-scale deployment with smaller equipment footprints or even energy harvesting solutions.

The first iteration of this deliverable, D8.5 Value Chain Pilot I marked the successful completion of MS13 with a first iteration of the COMPOSITION platform being effectively deployed and evaluated. With the completion of this document it will mark the successful completion of MS14.

2 Abbreviations and Acronyms

Table 1 - Abbreviations and acronyms used in the deliverable

Acronym	Definition
BLE	Bluetooth Low Energy
BMS	Building Management system
CMMS	Computerised Maintenance Management System
COTS	Commercial Off The Shelf components
DLT	Deep Learning Toolkit
DoA	Description of Action
DSS	Decision Support System
HMI	Human Machine Interface
IIMS	Integrated Information Management System
KPI	Key Performance Indicator
MTBF	Mean Time Between Failure
MTTR	Mean Time to Repair
PSU	Power Supplied Units
RSSI	Received Signal Strength Indication
SFT	Simulation and Forecasting Toolkit
SUS	System Usability Scale
UWB	Ultra-Wide Band

3 Introduction

3.1 Purpose, context and scope of this deliverable

The purpose of this deliverable is to report the status and outcomes of the final iteration of the industrial pilot focused on value chain. Five Value Chain use cases, 3 at BSL and 2 at KLEEMANN, have been implemented as demonstrators of the COMPOSITION platform and their description, planning and deployment will be presented. This document will also focus on the evaluation of those use cases in terms of technology assessment, human machine interfaces (HMIs) and risk analysis. This document is the final iteration and update of “D8.5 Value Chain pilot I”.

3.2 Content and structure of this deliverable

After the initial executive summary and contextualization on section 3, this deliverable starts reporting the Intra-factory Value Chain Centric Pilot demonstrators on section 4, with a description of the use cases implemented at BSL and KLEEMANN (for both set-up and information flow from the factory to the partners) and then reveals the Key Performance Indicators and metrics that are being used to extract and expose, in a user-friendly way, the information collected from the equipment.
After the use case explanation, the Value Chain Pilot evaluation is presented on section 5. First, with an on-site technology review for each use case, followed by the Human Machine Interface evaluation for each pilot. After the presentation of the risk assessments from all use cases and technology involved, the evaluation section is closed with an explanation of the synchronization between reality and simulation. The main content of the deliverable is then summarized in section 6 with the deliverable’s conclusion.

4 Intra-factory Value Chain Centric Pilot

4.1 Value Chain Use Cases: Set-up and Demonstration

4.1.1 UC-BSL-2 (Predictive Maintenance): Set-up

This use case aims to predict failures on BSL's reflow ovens. In order to achieve this, the COMPOSITION IIMS will collect a combination of the data outputted from those reflow ovens (real-time and historical) along with additional acoustic data outputted from TNI-UCC. The COMPOSITION IIMS will then use a combination of statistical models, algorithms and different machine learning technologies to attempt to predict a likely point in time when the machine would fail.

When BSL's Reflow ovens begin to fail, the motors often make high pitched noises. This acoustic data was therefore defined as useful data to collect to use in combination with the data the oven itself already outputs.

In order to collect this acoustic data, five of Tyndall's Raspberry Pi Micro Controllers fitted with acoustic sensors were installed near the motors in the Rythmia reflow oven. In the picture bellow (Figure 1), on the left shows one of these sensors and, on the right, the motors which the sensors are monitoring.

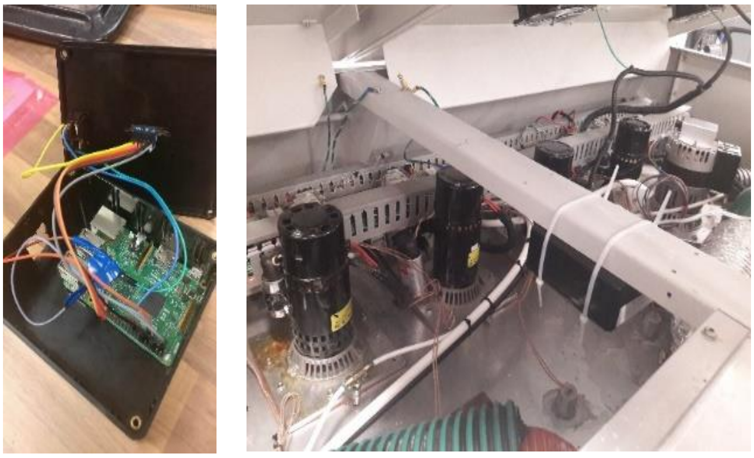


Figure 1- Set-up inside reflow oven

Initial tests were performed when two weeks of 'good' baseline data was taken while the sensors were installed in the oven. This data was then compared to 'bad' data which was collected from the reflow oven when a faulty fan was installed. This bad fan was installed at approximately 3pm on the 19th of February 2018 and it was removed from the oven by 3pm on the 21st of February 2018. This data was analysed by the partners to use as a reference and improve the failure predictability.

The diagram below (Figure 2) gives an overview of the complete acoustic system. The system is currently configured to support 5 acoustic sensors. Note that this is not a limitation of the architecture, more could be supported if a deployment required it. The five acoustic sensors are placed to detect noise from the 32 fans within the oven.
The sensor records 20 seconds of sound every 5 minutes as high-quality WAV files sampled at 48kHz. Each of these files is 3.7MB in size. This data (WAV files) is fed back to a PC on the manufacturing floor where the WAV files are stored on a 2TB external USB drive that would need changing every 12 months.

In the manufacturing floor PC, a MATLAB script was installed to calculate the mean amplitude of each 20 second recording and stores it as a decibel (dB) value in a CSV file. The WAV files and CSV files are time stamped to the PC clock on the manufacturing floor.

Each of the Raspberry PI's have 32GB SD cards installed. To prevent the memory cards from overflowing the system only keeps the most recent 10 files in memory.

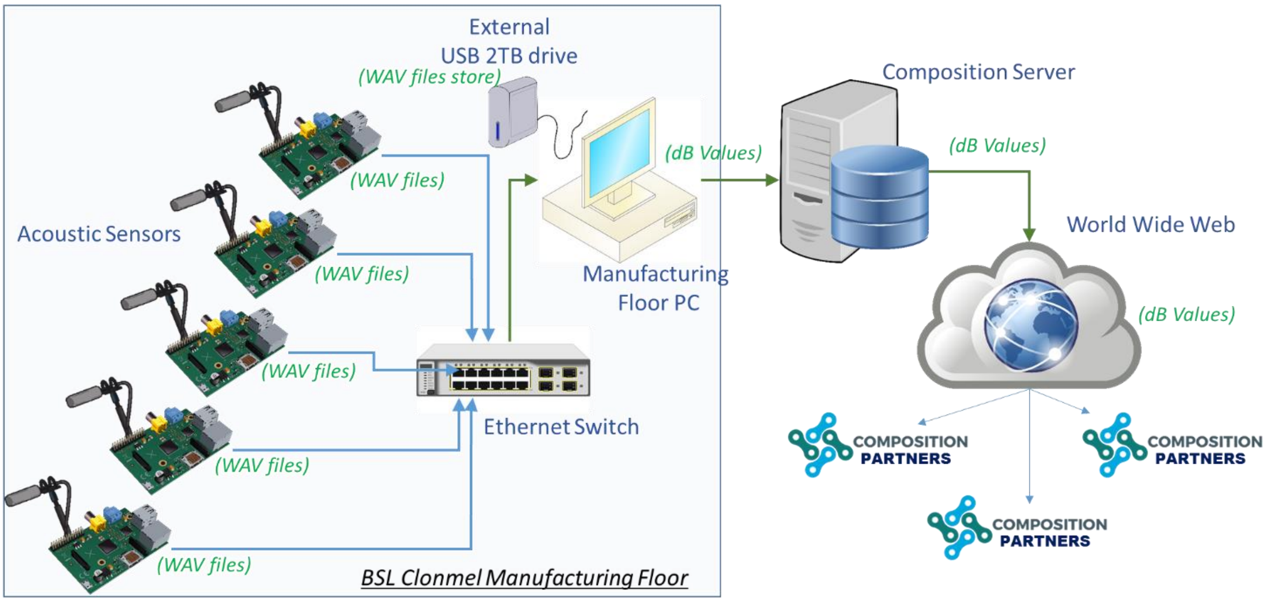


Figure 2 - Overview of the acoustic system

There are currently three sets of data being analysed:

1. The real-time data file from the Reflow oven (a new file is generated every five minutes that monitors Set Temperature, Actual Temperature and Output Power).
2. The real-time event file from our Reflow oven (a new event file is generated every five minutes. This file logs any event/warnings which takes place on the oven during that day e.g. Heat 17: Hi Warning 227°C.).
3. The acoustic data generated from the sensors that the partner TNI-UCC has placed inside the reflow oven (a new acoustic file is generated every five minutes)

As soon as new files are generated, they are sent to the COMPOSITION cloud where they become available to the rest of the partners. Three different COMPOSITION components analyse the results. BDA (Big Data Analytics) aggregates, annotates, filters and publishes data results for DLT.

DLT provides a prevision for the next possible breakdown with OGC ST and then propagates the possibility to the LA, which applies machine learning techniques for training the system and accepting only the correct predictions. The results are sent to the DSS which applies rules created in the Rule Engine to raise an alarm according to predictions and data. Also, rule application leads to different alerts through the DSS Notification Engine and according to those pre – set parameters, different notifications are sent to actors according to the rules in the Rule Engine. Finally, the rule results and data visualisation are shown in the DSS HMI.

The dBs levels data is also sent to the SFT which applies DBSCAN methodology for local outliers detection and enables the creation of a monitoring process. The monitoring process detects the outliers of the dB and when four consecutive outliers are detected for each fan, it creates and event and sends it to the DSS through DFM which holds the outliers as events. The rules in the DSS try to operate with the best practice, so more advanced rules combine the dB levels and the events from the outliers.

All components communicate between them through a message broker. The broker receives the data gathered on BSL shop floor through the BMS and distributes it through MQTT protocol to the rest of the COMPOSITION components.

There are two ways to structure the MQTT topics. These are: system infrastructure and semantics/domain model

- ***System infrastructure:***

  [component]/[Scope]

  Composition/BMS/NXW_51/OGC/1_0/Datastreams/ds_5-1/Observations

- ***Semantics / domain model:***

  [O&M:Procedure]/[DFM:Asset][O&M:ObservedProperty(DFM:Event.Type)]

  Composition/IntraFactory/Prediction/Task_0pf4jcq/Failure

MQTT topics are used for the intra – factory communication, while AMQP topics for the inter – factory communication.

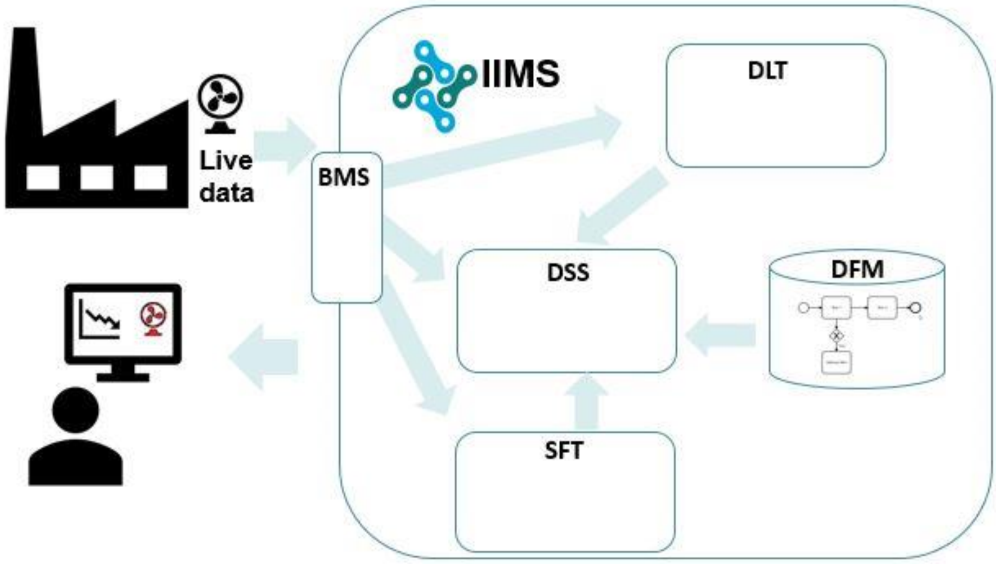


Figure 3 - UC-BSL-2 Information Data Flow

There is also security option in the UC. LinkSmart Service Catalog is used by Security Framework for PK (Port Knocking) management in order to define which ports in the system will be public and available to all, through opening them in the firewall. Also, ACL options for authentication and authorisation are applied to each component. The list provides the authenticated system users and those who are allowed to participate in the US, using its HMIs. SSO options have been discussed for the COMPOSITION project, in order a user to sign – on only once for the different components.

Security is provided to both event and message broker, where each component uses its own credentials to subscribe in the topics that accesses. If the components are able to subscribe with the given credentials, it has all the resources to access the topics and receive the data from them. On the other hand, when a component tries to subscribe to the message broker with faulty credentials, the broker recognises it and access is denied.

4.1.2 UC-KLE-1 (Maintenance Decision Support): Set-up

This use case focuses on the early detection of machine failure in the *BOSSI* polishing machine at KLEEMANN's shop-floor. A dataset generated by the Computerised Maintenance Management System (CMMS) is analysed. CMMS maintains a database including information about the company's maintenance operations, such as failure/problem description (mechanical, electrical, hydraulic), duration of breakdown repair, cost of machine breakdown repair, cost of person hours, cost of parts required for repairing etc. This set of data is extracted from CMMS in excel as a report file. 697 actions (breakdowns, preventive maintenance, machine improvements etc) have been recorded over a period of11 years (2007-2018). The probability of the type of the next breakdown to happen has also been calculated by utilizing time series.
A second set of data, is generated from the sensors that are installed outside of the *BOSSI* machine by CERTH. The sensors used to capture vibration data are accelerometers. More information about the sensor types can be found in *"D7.7 On site Readiness Assessment of Use Cases based on Existing Sensor Infrastructure II"*.

The vibration sensors that selected were the LIS3DH accelerometer sensor break out boards each connected via SPI bus with an ESP32 SoC with integrated Wi-Fi communication. If a Bossi motor is operating the vibration sensor is detecting its vibrations and performs a sampling of raw measurements in 3-axis that is immediately sent over Wi-Fi and MQTT to the Broker. The procedure is repeated as long as the Bossi motor is operating.

Figure 4 - ESP 32 board and Lis3DH on a Breakout Board

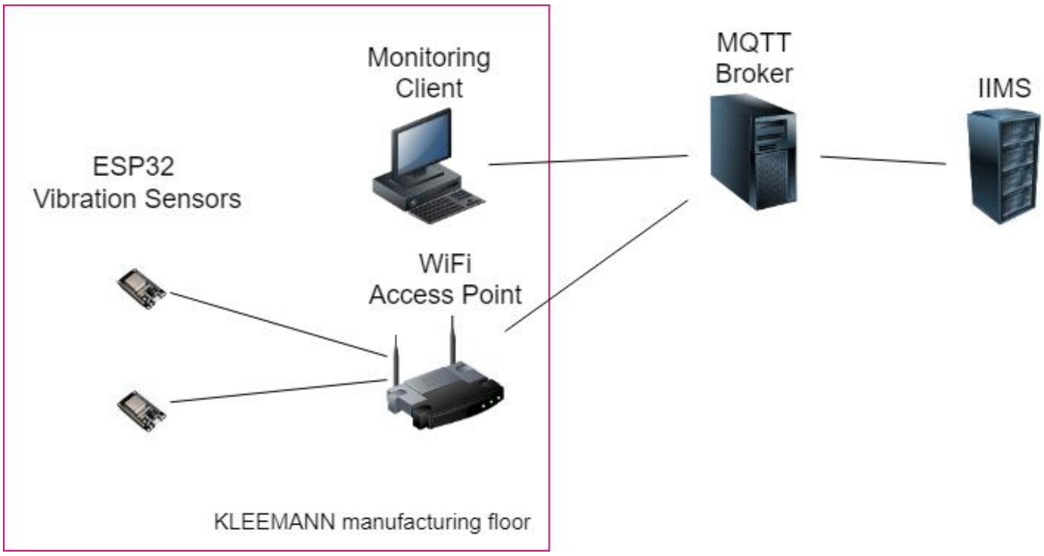


Figure 5 - UC-KLE-1 Sensors Network Architecture

The data of both datasets generated from CMMS and the installed sensors, is analysed together to give early indication that a motor inside or outside of the BOSSI machine will face a near future breakdown. This is then communicated to the maintenance planner and maintenance manager via email or via the COMPOSITION platform. KLE is currently in the process of defining thresholds for the failure notifications in the *BOSSI* polishing machine.

Vibration data from BOSSI machine is gathered from the sensor network and is stored in the BMS. Using OGC SensorThings format, data is propagated to all other COMPOSITION IIMS components. MQTT and AMQP topics are also used in the distribution of information and delivery of data to the components. Information and data are delivered the same way as in UC–BSL-2 Predictive Maintenance for BSLData would be used by SFT in order to produce prediction results. A Machine Vibration Diagnosis Profile algorithm has been implemented in SFT in order to discover in real-time abnormal operation of motors from BOSSI polishing machine. Finally, SFT propagates the data to DSS for rule creation and knowledge extraction and to Visual Analytics tool for visualization and monitoring. KPIs will be created for UC-KLE-1 Maintenance Decision Support, as well as data visualisation from the DSS.

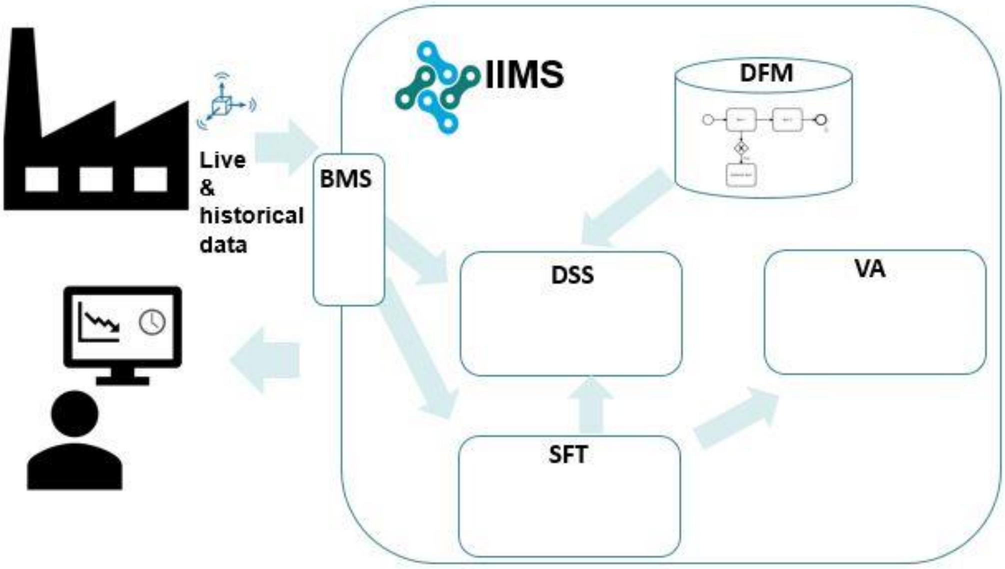


Figure 6 - UC-KLE-1 Information Data Flow

The data coming from the visual analytics toolkit is the transformation of the raw vibration data. The vibration data is measured as acceleration over the three axes, *x,y,z*, and their transformation is the eigenvalues of the accelerations. These eigenvalues show outliers in the data that may be possible failures for the system, if there are continuously recurring.

DSS uses rule engine for decision making process and the extraction of knowledge. KPIs are used for knowledge measurement and data visualisation is another objective of the DSS.

4.1.3 UC-BSL-3 (Asset Tracking): Set-up

This use case aims to allow the tracking of equipment across the BSL facilities. As a manufacturing site, the environment inside the production floor is very fast-paced, which leads to several pieces of equipment ending up being misplaced or missing (component trays that are placed in the incorrect destination, devices that need manual rework and are temporarily removed from the line, equipment sent for calibration, etc.). In order to track equipment and know where each component is at a specific time, a real-time tracking system is being implemented and tested by TNI-UCC.

For the value chain pilot, the tracking system was installed in a prototyping area in BSL. On Figure 7, a photo of that prototype area is shown on the left and the equipment being tested on the right. This location was chosen to facilitate evaluation and development of the system without disturbing the normal manufacturing process and avoid all the logistics and requirements that would be needed if we decided to include a new frequency generating system in an extremely regulated electronic medical device manufacturing line.

Figure 7 - Tracking system (right) and prototyping area (left)

External frequency measurements were performed in order to create the baseline for “background noise” and check interference with the Airfinder tracking system. A plan was already designed by TNI-UCC and the several components of tracking system were installed. The readers on the ceiling, the gateways on a bench in the centre and the tags on the equipment to be tracked.

The diagram below (Figure 8) shows the Airfinder BLE asset tracking system which is being tested at BSL. This system uses proximity as the basis of asset tracking (as opposed to trilateration / triangulation). The protocol used is BLE (Bluetooth Low Energy) and RSSI (Received Signal Strength Indication) indicates which reader the Tag is closest to.

Each reader is at a known location, the Tag is attached to the item to be located. As the tag moves around, the readers will measure the RSSI and report this back to the gateway. The gateway then indicates which reader has the highest RSSI and thus it is assumed the tag is in that reader’s area. The higher the density of readers in a room the better the resolution of position determined.

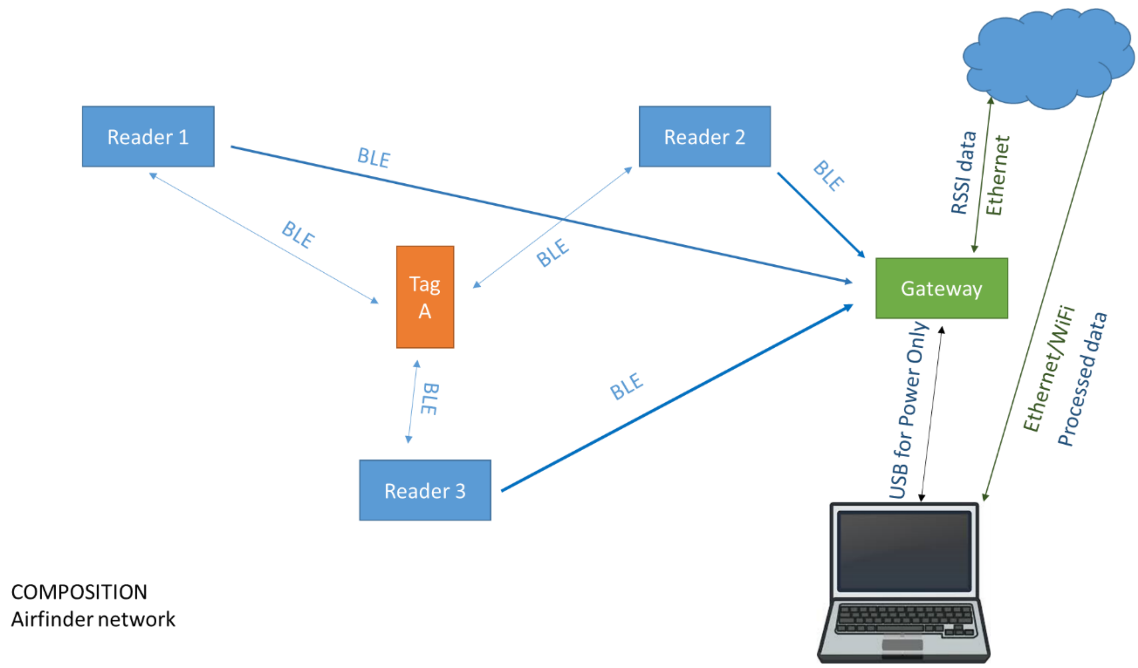


Figure 8 - Diagram of Airfinder’s information flow

4.1.4 UC-BSL-5 (Equipment Monitoring and Line Visualisation)

This use case focuses on displaying an analytic view of all assets of the production line (relevant information on the equipment, products currently on the line, flow of the product through the lines, etc.) on a visualisation screen on the factory floor.

There is no reliable way to track equipment up/downtime or the production hours lost due to equipment issues. An automated record would display how long which equipment is down or in alarm state and how that translates into the rest of the production line.

Logged in users can retrieve the history and performance of the equipment (uptime/downtime (green/amber and red state), and production compared to build plans (units processed per time period, target, quantity) from a GUI. Additionally, comments can be entered and retrieved from the system which are intended to give updates on equipment status to interested personnel and keep track of what measures are/have been taken to fix the equipment downtime.

The equipment/line information is pulled directly from BSL’s MES (manufacturing execution system) in a .csv format, processed by COMPOSITION and the final result displayed on a visualization screen, with the following flow of information (see Figure 9)

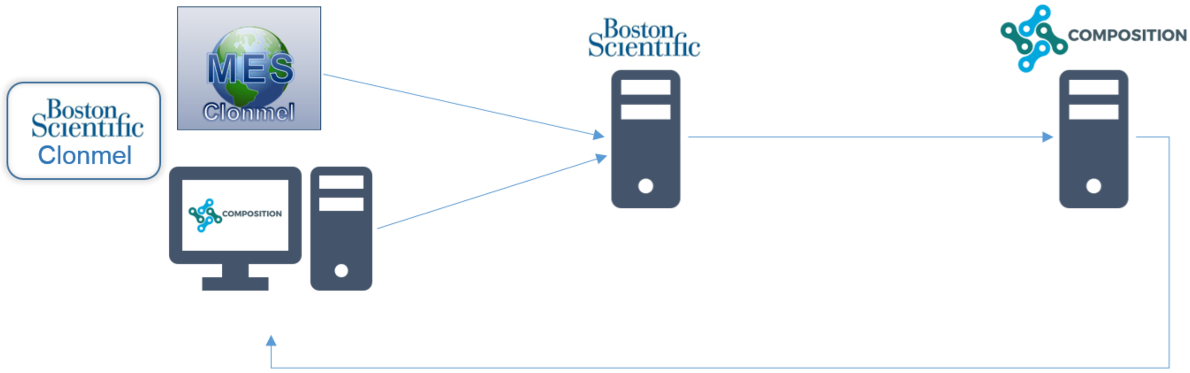


Figure 9 - Information flow for UC-BSL-5

4.1.5 UC-KLE-3 (Scrap Metal and Recyclable Waste Transportation)

This use case focuses on the detection of bin and container fill levels and the calculation of the optimal route for collecting bins inside KLEEMANN's shop-floor. The installed sensors provide early (real-time) notification of the recyclable and scrap metal bins fill levels and suggest optimal routes for collecting bins within the factory. Overall, minimization of the total distance from bins to container and improvements in containers' fill level management are expected.

The Scrap Metal and Recyclable Waste Transportation is triggered by a full bin in KLEEMANN's shopfloor. In order for the Prediction engine to be able to estimate and propose the optimal path to follow for the transportation of waste to a central bin outside the production line, a fill level sensor for the internal bins has been designed and developed. A total of 14 fill level sensors are deployed, 12 are installed on 3 sets of 4 bins containing recyclable materials (plastic, paper, aluminium and cardboard) (see Figure 10) and the other 2 are installed on bins containing scrap metal (Figure 11). In order to mount the fill level sensor a metal branch was created by KLEEMANN and a 3D printed case for the sensor was created by CERTH.

Figure 10 - 3D Printed Case and Metal Branch (recyclable waste bins)

Figure 11 - 3D Printed Case and Metal Branch (scrap metal bins)

The shop-floor connectivity is depicted on details in the next figure:

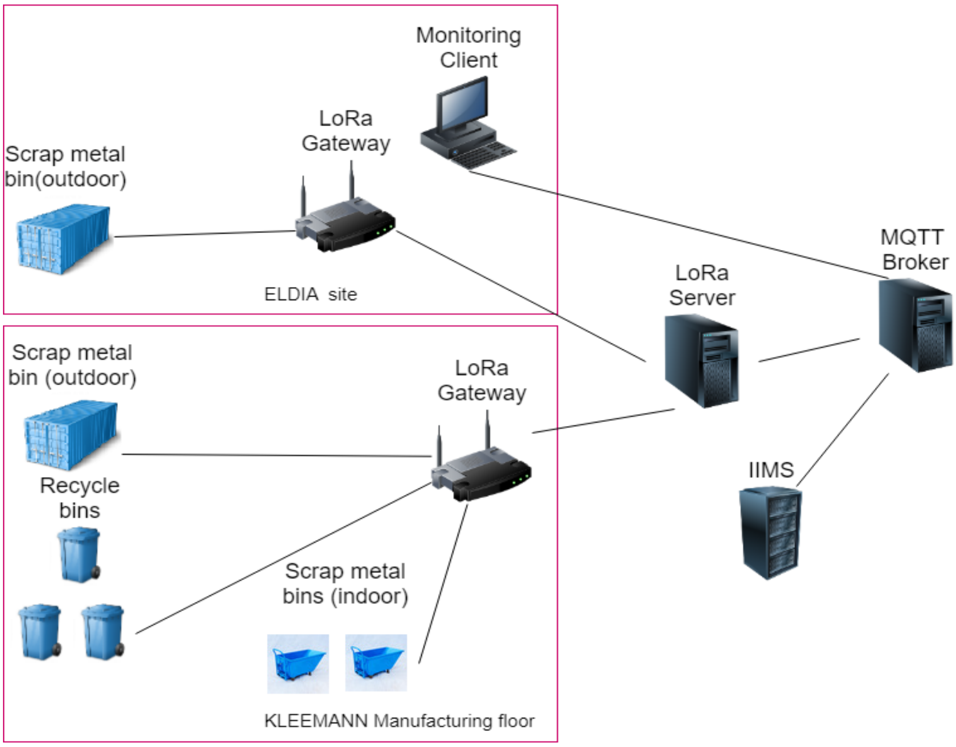


Figure 12 - UC-KLE-3 Sensors Network Architecture

In this case, the SFT monitors the data related to sensors fill level (available on BMS) and as soon as the measurement is over 80% an algorithm for the optimal route transportation is generated. The algorithm outcome that contains the points in KLEEMANN factory that a worker should visit in order to collect in optimal route the bin becomes available as an event on DSS. Then DSS sends a notification to the worker using an Android application. Furthermore, monitoring of all bins equipped with fill level sensors are available in COMPOSITION IIMS.

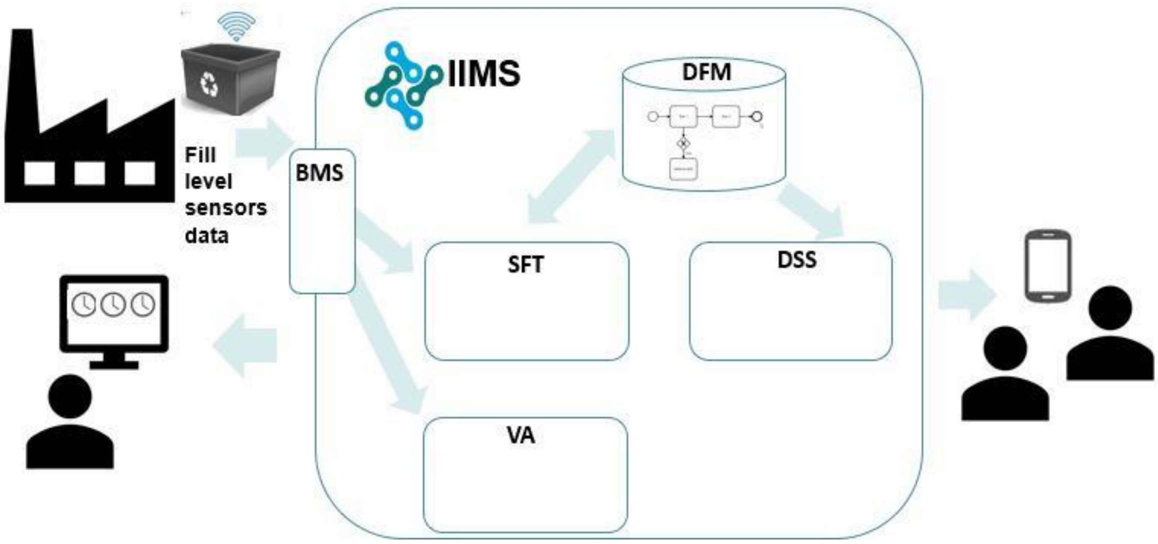


Figure 13 - UC-KLE-3 Information Dataflow

4.1.6 Data collection

COMPOSITION Value Chain use cases aim to generate value-added services (e.g. identify potential field issues, data processing, decision system, etc.) leveraging on the integration, correlation and aggregation of data from several heterogeneous data sources with different meaning. In fact, the data is collected in real-time by sensors, acquired from existing stores or also made available by direct observations and worker interviews.

Each application chooses the best approach to build its own datasets depending on the needed processing models and algorithms; however, a well-defined approach for data collection is of paramount importance to ensure:

- a comparable level of details and granularity for the data;
- a common interpretation of the data;
- communications conformity among interconnected components.

The following datasets (Table 2) have been identified for UC-BSL-2 use case:

Table 2 - Dataset for UC-BSL-2

Type	Description	Format	Interval
Acoustic data	Each sensor records 20 seconds of audio data and every 5 minutes to calculate the amplitude in dBs	The amplitude is stored for each of the 5 sensors in a single timestamped CSV file.	Data from three different trials is available in the following intervals: • from 10 January to 16 January 2018 • from 16 January to 4 February 2018 • from 16 February to 9 March Data started being sent to the cloud since: May 2018

Oven sensor	Each blower logs two values: the measured temperature [°C] and the output power at the solid-state relay of the reflow. Records are sampled every 5 minutes.	Textual data structured as a list of records, one per row. Each row is timestamped.	Historic Data since; November 2013 Data started being sent to the cloud since: May 2018
Oven events logs	The list of events occurred in the oven (e.g. status, used recipe, warning, etc.)	Textual description of the events, one per row. Each row is timestamped.	Historic Data since; November 2013 Data started being sent to the cloud since: May 2018
Workers feedback	Operators can provide feedbacks based on experience, to correctly identify and solve a problem	Data aggregation rules and constraints (e.g. several consecutive warnings can be considered as an oven fault)	-

Table 3 - Dataset for UC-KLE-1

Type	**Description**	**Format**	**Interval**
Vibrometer data	Each vibrometer records acceleration over the three axis (x,y,z), during the operation of the BOSSI machine. The sample rate is 1344 records per second.	The data is transmitted directly through Wi-Fi. It is also propagated by the MQTT message broker to the IIMS components.	Live data since March 2018
CMMS data	Historical data extracted from KLEEMANN's CMMS system and provide information about failures on the BOSSI machine over the years.	Textual data structured as a list of records, one per row. Each row is timestamped.	From 2007 to 2018

Table 4 - Dataset for UC-BSL-5

Type	**Description**	**Format**	**Interval**
MES log files	Data for the MES on the shop floor. It contains job order and material description and equipment status on the production line. It also contains several fields providing a detailed description about the line status and production order	Textual data structured as a list of records, one per row. Each row contains an increasing number. The data set is extracted in CSV file format.	From February 2019

Table 5 - Dataset for UC-KLE-3

Type	Description	Format	Interval
Fill level sensor data	Data is continuously being sent to the BMS. It is described a percentage indicating the fill level of the scrap metal and recycling bins.	JSON files transmitted through the BMS	Live data since November 2018

4.1.7 Deep Learning Toolkit

The Deep Learning Toolkit (DLT) represents a point of intelligence aggregation in the COMPOSITION ecosystem providing predictions and forecasts of relevant indicators for predictive maintenance. In order to achieve a state-of-the-art prediction accuracy, artificial neural networks need to be extensively trained over large datasets. More details are available on deliverable "*D5.3 Continuous Deep Learning Toolkit for real time adaptation I".*

The shaping of a dataset, suitable to be used for Deep Learning Toolkit requirements and tailored for COMPOSITION's use cases, has initially started using only the oven sensors data. This activity has been demonstrated at the second review meeting at M19. Thereafter, the prediction models have evolved with even more complete datasets as the project grows and new information become available. In particular, suggestions from the BSL oven operators have been taken in to account to better identify failures causes and to improve the quality of the predictions.

The acoustic data, acquired in the last stages of the project, have been proved extremely useful to extend the information gathered from the oven sensors. Due to the limited acoustic data time intervals, synthetic samples have been generated, oversampling the existing information, to make the acoustic dataset range to span the full interval of the ovens' historical logs.

The resulting comprehensive dataset has been identified in order to create a suitable mapping of this information to be inputted to the DLT. In specific, a table of 242 columns was aggregate and qualitatively and quantitatively characterized. Each table row can be split in the four parts as shown below (Table 6):

Table 6 - DLT input table rows data structure

0	1	2	3	…	39	40	41	41	43	44	45	…	234	235	236	237	238	239	240	241

The leftmost part of the row (green, columns from 0 to 39) contains the values sampled from different oven sensors, measured at the same time. The central part (red, columns from 40 to 235) contains the mapping of the correspondent events. The rightmost part of the row (blue, columns from 236 to 240) contains the decibel values of the five acoustic sensors, registered at the same time of the corresponding sensors readings.

Operators' feedbacks provided at M22 has allowed refining the definition of failure, providing an insightful view of the procedure evaluation at the shop floor level, concerning the predictive maintenance scenario. This activity has been reflected directly into the dataset, with a comprehensive definition of states. In fact, the last column (241) contains a label that reflects this oven status. It can assume three values:

- 0 if the oven is working normally;
- 1 if a warning occurs;
- 2 if a failure occurs.

This value is used only for the artificial neural networks training phase.

At the moment, models based on this dataset structure have been created and tested on the real historical data gathered from BSL trials, however needing further refinements before the final deployment. More details about model effectiveness is described in "*D5.4 Continuous Deep Learning Toolkit for real time adaptation II"*.

4.1.8 IIMS

The Building Management System is a complex system that requires specific configurations to be put in place before running in a shop-floor. It is usually deployed on a local server physically placed in the installation site or in the cloud (or both), and its setup depends on the hardware installed in the building. For COMPOSITION, the best choice is to deploy the BMS as a cloud service, for two main reasons: the first is the cloud nature of all the ecosystem, the second is the geographical distance that occurs between the provider partner and the pilots (it's easier to configure, test and maintain the software this way).

Therefore, the BMS runs on a separate server, leveraging on a MQTT broker for handling communications with the intra-factory components. Shop-floor side, the data is collected through direct MQTT connection for the KLE pilot (Figure 14) and by transferring log files via sftp, with respect to the BSL pilot (Figure 15). Thus, the BMS that processes and forwards the live information is the same instance.

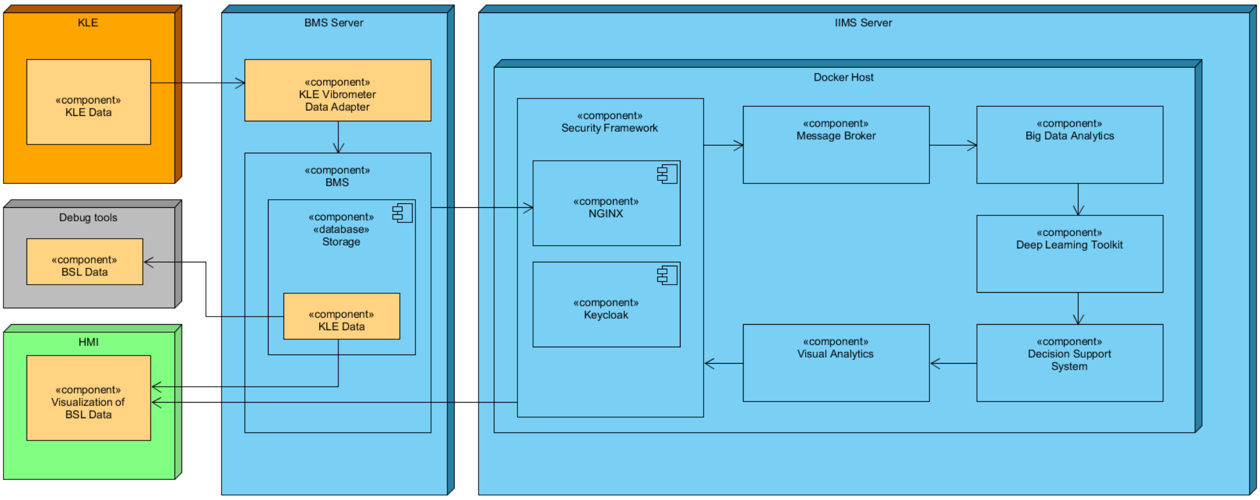


Figure 14 - KLEEMANN's use cases deployment

For UC-KLE-1 Maintenance Decision Support use case, a specific software adapter has been implemented and deployed inside the BMS server, in order to format the data to be handled by the BMS itself. The limitations of the hardware used on site made it necessary.

For both UC-BSL-2 Predictive Maintenance and UC-BSL-5 Equipment Monitoring and Line Visualisation use cases, since it was not possible to get live information from the devices, due to strict security rules of the pilot partner, log files of legacy systems and acoustic sensor data files are transferred in the BMS Server via SFTP and then the BMS is fed with this data by a software script.

Moreover, the BMS is exposing an interface for querying the internal storage, for data of both pilots, mainly for debug purposes.

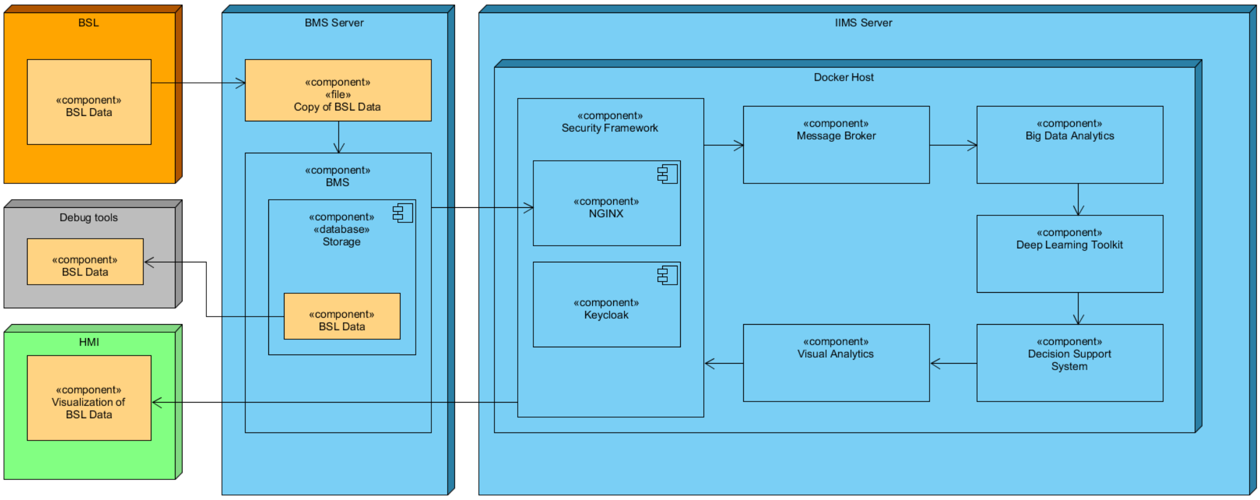


Figure 15 – BSL's use cases deployment

4.2 KPI's and metrics

Key Performance Indicators (KPIs) are used to measure performance in manufacturing processes. One of the major roles in creating KPIs for those processes is using data coming from sensors on the shop floor to measure pre-defined values, suitable for manufacturing KPIs. Also, the data can be used as input to the Decision Support System (DSS) and the outputs can provide measurements and statics that create KPIs concerning the decision-making process on the shop floor. Both roles rely heavily on data existence and the relation that might exist between it.

There are different ways to choose a set of KPIs for certain processes. Decision makers or managers should choose from:

- a fully certified KPI set such as: BREEAM, Open House, Super Building etc[1]
- Select KPIs from existing sets
- Add new KPIs when existing and certified sets do not satisfy the needs for a specific case

Decision making process is highly iterative and many results may appear in later iterations. New KPIs should cover these iterations. Another fact that should be taken into consideration is the combined knowledge that KPIs provide and how this abstract notion should be reformed to KPIs.

The context and content of data on different shop floor lead to the implementation of different KPIs, both as visualisation and decision-making tools. One example is two different factories, use the same machine and the same monitoring sensors. The first one uses the machine in a very stable environment and the slightest changes in its operations lead to problematic situations and the need for maintenance processes or changes in the manufacturing process in order to prevent faults. The second machine is located in a heavy working environment, which implies heavy and unstable use of the machine. Small changes in data do not affect the manufacturing procedure. In both cases, the produced data is the same, but the purpose of the machine is different in the two shop floors and the resulting KPIs for the machine operation should be different.

There are different models applied on shop floors for different procedures. There are models about manufacturing processes, maintenance processes, security and safety processes that should be considered when creating KPIs in a DSS. While there may be some actors, assets and tasks that are the same on all shop floor processes, there are some that exclusively belong to different processes. Applying a set of KPIs, those factors should be implemented.

Finally, creating a set of KPIs should take into account the person that will see the KPIs and learn something from it. Different information is considered useful for workers, technicians, safety actors, decision – makers or managers. The suitability of the provided information to different actors should be one of the main aspects to consider while creating or setting KPIs.

4.2.1 KPIs in the COMPOSITION DSS

COMPOSITION DSS has a dual functionality. The simpler one is to visualise the incoming data and create graphs and charts indicating the operational status of the shop floor. The second one is to use a DSS in the decision – making process. In both functionalities, live data is available that can be used for the KPIs. Use case and model analysis should lead to the KPIs which will be used by COMPOSITION DSS and provide knowledge for the shop floor and maintenance procedures. For each use case, the KPIs should provide information to all different actors, or be extracted and become further knowledge for the DSS.

4.2.2 KPI's from the DoA

The individual use cases are evaluated against applicable KPIs as these are defined in the Description of Action, see Table 7. The numbers in column 2 are added for easy reference in Tables 8-12.

Table 7 - KPIs from DoA

Area	Key Performance Indicator	Target
Improvement from collaborative, real-time efforts towards down-time and logistics inefficiencies (affects **availability**)	1. Overall reduction in down-time from failures & bottlenecks	15%
	2. Cost savings for process monitoring	25%
	3. Reduction of amount of non-critical spare parts availability	10%
Improvement from enhanced integration of manufacturing and logistics processes (affects **performance**)	4. Reduction in cycle-times from process monitoring & behaviour	10%
	5. Better interaction with the suppliers, recycling companies	10%
	6. Cost improvements from improved process monitoring	25%
Improvement in manufacturing quality from modelling, simulation and communication (affects **quality**)	7. Improvement in manufacturing quality	5%
	8. Reduction of order-to-delivery time and shipping costs	10%
	9. Reduction in scrap and repair costs	50%
Innovative services, models and practices optimising manufacturing and logistics processes (Improved **business** and innovative service models)	10. Number of new, sustainable business models developed in the project	5
	11. User acceptance ratio of validated ICT security and trust measures	>95%
Reductions expected in the efforts for integration or reconfiguration of today's automation systems	12. Total reduction in the efforts for integration or reconfiguration	30%
	13. Improvement of non-effective procedures with decentralisation	20%
	14. Reduction in time for optimisation of products/services	10%
Improved reaction to market changes using holistic global and local optimisation algorithms	15. Improvement in time-to-market ability	15%

4.2.3 UC-BSL-2 Predictive Maintenance

The basic analysis concerning the KPIs is based on the assumption that there are three separate entities that can define specific KPIs. The entities are: the incoming data, the most important and most occurring failures, time periods. From these entities, we can extract KPIs based on the time periods as the period in which we count the indicators and the second value is a combination of the incoming data and the failures.

Incoming data

- Sensor temperature
- Set point temperature
- Power consumption
- Noise

These inputs should be connected with the failures occurring on the shop floor. According to the log files the most occurring failures are:

Failures

- Oxygen concentration has exceeded the amount set for alarm
- Heat: Low, Medium, High warning
- Acknowledge all alarms
- Noise level limits

Table 8 - KPIs for UC-BSL-2

<table>
<tr><td>KPI</td><td>Target</td><td>Pre</td><td>Post</td><td>Change</td><td>Units</td></tr>
<tr><td rowspan="2">1.Overall reduction in down-time from failures & bottlenecks</td><td>15%</td><td>Up to 5</td><td>Up to 3</td><td>>= 40%</td><td>Downtime Associated with failure (hours)</td></tr>
<tr><td colspan="5">Pre – Downtime can take up to 5 hours depending on the location of the fan.

Post – This time is reduced to a maximum of 3 hours.
Assuming all fan failures will be predicted, the reduction in time to deal with a fan related issue will be 40%.
With the current prediction window, a repair might still have to occur during production active hours. However, with the future increase in the prediction window, this would be dealt exclusively outside production time, so this could be decreased and will be considered maintenance only and not actual productive downtime.</td></tr>
<tr><td rowspan="2">2.Cost savings for process monitoring</td><td>25%</td><td>3</td><td>2</td><td>33%</td><td>Number of Maintenances per year</td></tr>
<tr><td colspan="5">With the fan failure prediction, the new generated data and analyses, the number of maintenances can now be optimized and reduced (this is not a final number since before any process is altered, it needs to go through a maintenance change approval process that needs to be approved by the process development team as well as the regulatory team. Due to the nature of the products that Boston Scientific manufactures, those decisions need more than one year of stable data). From what we’re assessed so far, the preventive maintenance procedures can be reduced to the minimum.</td></tr>
<tr><td>9.Reduction in scrap and repair costs</td><td>50%</td><td>

3</td><td>

2</td><td>50%

33%</td><td>Pre: Costs for scrappage due to equipment failure + Scrappage costs from</td></tr>
</table>

				Overall: 42%	other non-compliant materials Post: Fan failure being predicted and reduced unscheduled maintenance
	No fan failures occurred during the time that data was being collected. However, the system has been giving correct prediction and is working properly. Scrappage of non-compliant material will always occur, however, since 50% is usually attributed to manufacturing equipment failures, we can confirm the prediction of 50% of reduction costs due to scrapped material is valid. As well as scrap, there is also a reduction in repair costs as less maintenance will occur, looking at the amounts of unscheduled maintenances per year.				
12.Total reduction in the efforts for integration or reconfiguration	30%			25%	Qualitative
	When we mentioned 30% to the personnel in charge of the evaluation of the composition platform, they mentioned there are usually 4 main common causes of oven failure: fan, traveller belt, heaters and exhaust. Eliminating one of the possible causes when a failure occurs, will naturally lead to a 25% reduction in time analysing if the oven failure was due to a faulty fan. Pre- Alarm would be triggered by any overall failure in the equipment (fan or otherwise) and a technician would have to analyse where the failure happened and assign it to the correct maintenance technician Post - Specific fan failures are now predicted (as well as specific alarms are displayed on the COMPOSITION interface) so the time to detect if the failure was due to a faulty fan				
14.Reduction in time for optimisation of products/services	10%			33%	Same as KPI2
	It is easier for the technician to preform repairs. as mentioned on KPI2, the preventive maintenance frequency can now be reduced to the minimum, which lead to a 33% improvement in optimization				

4.2.4 UC-KLE-1 Maintenance Decision Support

The basic analysis concerning the KPIs is based on the assumption that there are three separate entities that can define specific KPIs. The entities are: the incoming data, the most important and most occurring failures, time periods. From these entities, we can extract KPIs based on the time periods as the period in which we count the indicators and the second value is a combination of the incoming data and the failures.

Incoming data

- Live data from vibrometer
- Live possibility of failure for the BOSSI machine, based on historical data retrieved from the CMMS, for the next 24 hours
- Historical data containing failures on the BOSSI machine, coming from KLEEMANN's CMMS

This incoming data is connected with the failures happening on the BOSSI machine on KLEEMANN shop floor. According to the historical data the most common failures to happen are:

Failures

- Mechanical Failures
- Electrical Failures
- Hydraulic Failures

Figure 16 shows the graph of the KPI MTBF for the *BOSSI* machine on KLEEMANN shop floor. The KPI is visualised in a time series and it is plotted for 7,5 years. There are options allowing the user to define the time period the KPI should be computed, as well as the way the KPI is computed.

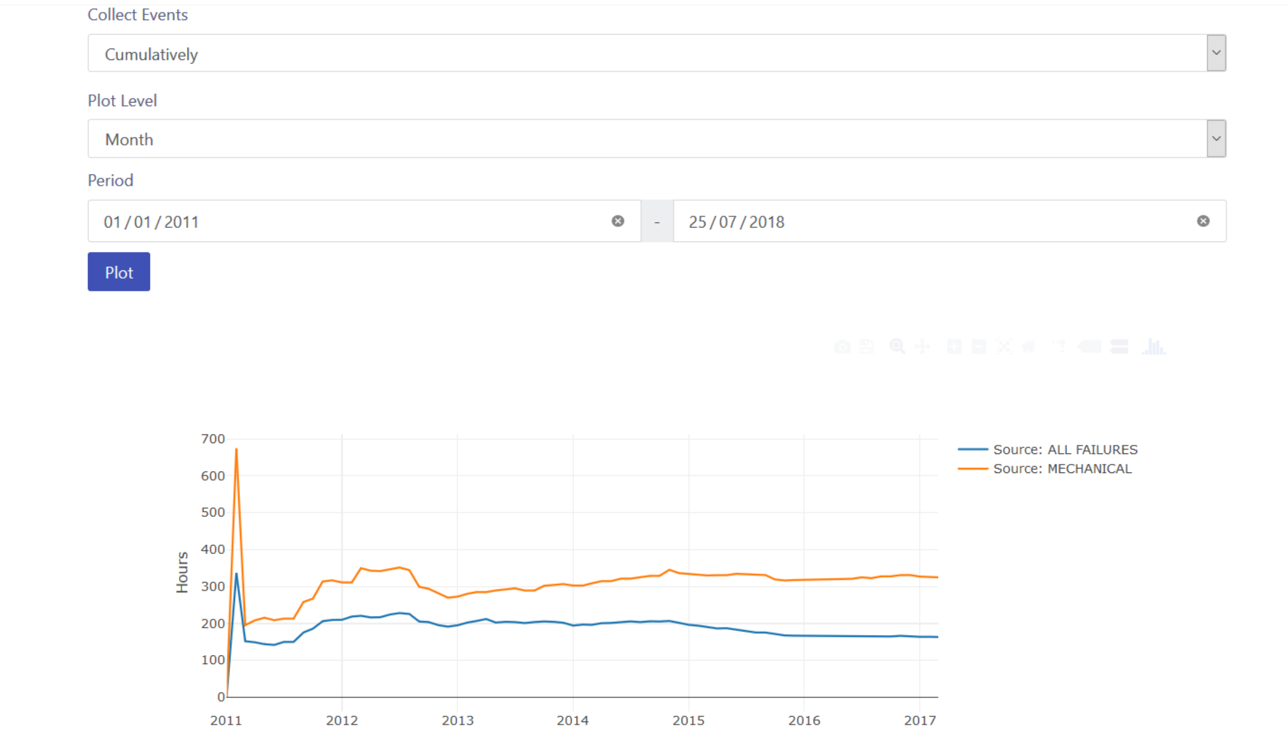


Figure 16 - MTBF of BOSSI Machine

Table 9 - KPIs for UC-KLE-1

<table>
<tr><td>KPI</td><td>Target</td><td>Pre</td><td>Post</td><td>Change</td><td>Units</td></tr>
<tr><td rowspan="2">1.Overall reduction in down-time from failures & bottlenecks</td><td>15%</td><td>3.5</td><td>3</td><td>14%</td><td>Hrs
(down-time from failures)</td></tr>
<tr><td colspan="5">The result is based on 10 years of historical data and 1 year of live data, which unfortunately does not include a statistically significant number of failures. This is indicated by a number in brackets. Another issue is that measuring the vibration amplitude is not sufficient to predict failure of the Bossi machine.

A more realistic expected outcome is a 5% reduction in down-time with predictive maintenance compared with preventive maintenance.</td></tr>
<tr><td>2.Cost savings for process monitoring</td><td>25%</td><td>1520</td><td>960</td><td>37%</td><td>Euro
(Cost of person hours and parts)</td></tr>
</table>

	The result is based on 2 sets of CMMS data. The first set includes the annual cost of person hours and parts related to the polishing machine before the installation of sensors. The second set includes also the annual cost of person hours and parts, but after the installation of sensors and the monitoring of the vibration profile via the COMPOSITION IIMS. Despite the fact that there were no significant failures in the monitoring period, this cost improvement can be attributed to the process monitoring provided by COMPOSITION.				
7.Improvement in manufacturing quality	5%				
	Quality is a very broad concept depending on numerous factors, and therefore difficult to measure. A relatively simplified measurement for UC-KLE-1 could be the number of defects in the piston production line. As for KPI 1, the insufficient amount of live data means that improvement in manufacturing quality presently cannot be attributed to the application of COMPOSITION.				

4.2.5 UC-BSL-3 Asset tracking

Incoming data

- Live location of the tagged equipment

Table 10 - KPIs for UC-BSL-3

KPI	Target	Pre	Post	Change	Units
6.Cost Improvements from process monitoring	25%			85%	See below
	Pre – This was a non-existent process. On average, 25% of the equipment due for calibration, misses the calibration deadline because it was missing at the time due to misplacement. Post- After studying the limitations of the technology and adjusting accordingly, all the tracked equipment was always detected. With a small percentage of the costs going towards the tags and beacons and running the system.				
14.Reduction in time for optimisation of products/services	30%	45	10	77.78%	Time/minutes
	Pre - The time it takes to find the equipment can vary a lot from minutes to days. Post – Current time spent is greatly reduced, logging into the COMPOSITION system + finding equipment – 5-10 minutes				

4.2.6 UC-BSL-5 Equipment Monitoring and Line Visualisation

Incoming data

- MES log files

Automated data transfer is not currently in operation so the KPI's are based on the manual file transfer to the cloud. With every manual data transfer, the system allows a full line visualization where it will be easier to see which equipment is free and can be optimized or where the bottleneck is originating.

Table 11 - KPIs for UC-BSL-5

KPI	Target	Pre	Post	Change	Units
1.Overall reduction in down-time from failures & bottlenecks	15%	30	20	33%	Time/minutes
	Pre - Login to 2 different manufacturing management systems + navigate through confusing GUI + create a query to obtain the info from specific machines + analyze information and decide Post - Manual daily file transfer to the cloud + Logging into the COMPOSITION system + analyze info and decide				
6.Cost savings for process monitoring	25%			33%	Same as above
	Assuming the same performance as in KPI 1, and knowing the time saved will be a direct translation into cost savings, the same improvement percentage will also apply to costs				
9.Reduction in scrap and repair costs	50%				
	System will not run long enough to produce significant results for UC-BSL-5				
14 Reduction in time for optimisation of products/services	30%			33%	Same as above
	System will not run long enough to produce significant results. Assuming the same performance mentioned on KPI 1, the same improvement percentage will also apply to manufacturing optimization: 33%				

4.2.7 UC-KLE-3 Scrap Metal and Recyclable Waste Transportation

Incoming data

- Live data from fill level sensors

Suggested KPI

- Cost improvements from improved process monitoring

Table 12 - KPIs for UC-KLE-3

KPI	Target	Pre	Post	Change	Units
6.Cost Improvements from process monitoring	25%	260	250	4%	L/month (Fuel consumption)
	The forklift's fuel consumption and cost (per month) was reduced by 4%. With the same quantity of recycling materials, this cost improvement can be attributed to COMPOSITION. However, we need more time and evaluations of the application to be more accurate. Also, 5 out of 15 stations are monitored in the central factory. Further improvement is expected in the future if we install the system in all of the recycling bins.				

5 Value Chain Pilot Evaluation

5.1 On-site technology

5.1.1 UC-BSL-2 (Predictive maintenance)

Overall, the technology implemented has been working without any issues and is being delivering the expected performance. However, for a future large-scale deployment, whilst the current configuration enables flexibility and easy reconfiguration using readily available off the shelf parts, the overhead to maintain, together with the scalability of such a system would be a challenge in a larger site wide deployment.

The prototype system as deployed requires significant infrastructure for operation. The raspberry Pi requires powering for mains sourced powered supply units (PSU). In a highly regulated manufacturing environment, it is essential to reduce the amount of clutter and cables, the raspberry Pi system requires mains PSUs with associated extension leads and PSUs to be managed. In addition, data is communicated via Ethernet, this requires a cable for each raspberry Pi and associated Ethernet switch to return the data to the Manufacturing Floor PC. Replicating this across multiple ovens on a large manufacturing floor would be extremely challenging. A production version of the system should be battery operated, physically smaller and use radio to send data back to the Manufacturing PC (Although radio transmissions in highly regulated environments can be challenging).

With regards the operation of the system. Today WAV files are sent to the manufacturing floor PC for processing. The processed data is then sent to the COMPOSITION server. WAV files are only required at present for research purposes, the transmission and storage of such a large quantity of data would be unnecessary in a production version.

5.1.2 UC-KLE-1 (Maintenance Decision Support)

After a firmware update, the sensor now does sampling at 1.344 kHz, as opposed to the previous 5 kHz. The number of samples in each sampling window/json object is now 1344 samples/axis, from 500 samples/axis. When the BOSSI motor is on (and when there are no connectivity issues), the json object format remains the same, however it is noted that the size of each object will be much bigger. Also, the data rate is now 1 json object/1-2 seconds, as opposed to the previous 1 json object/15-20 seconds. The applied changes give better data precision as well as more functional coverage since the measurements are more frequent.

This firmware update was done remotely using the firmware update using the device's "over the air" feature. On-site feedback has been given by KLE regarding the sensitivity calibration of the sensor. Five different sensitivity levels were tested. A compromise was made between being too sensitive (and capturing vibration noise from sources other than the functioning *BOSSI* machine) and being too insensitive, to only capture BOSSI activity that triggers the device.

5.1.3 UC-BSL-3 (Asset Tracking)

As in UC-BSL-2, the technology implemented has been working without any issues and is being delivering the expected performance. However, challenges with proximity based systems using RSSI relate to multipath giving erroneous results and scalability. For example, to get an accuracy of +/- 2m the readers would need to sit on a 4m grid. For a manufacturing floor of 100m x 100m, 625 readers would be required.

Other techniques exist using UWB (Ultra-Wide Band) or phase difference of arrival techniques which are more resilient to multipath but these systems are less mature and power hungry compared to BLE.

To move the asset tracking to a commercial plane in BSL challenges would be associated with scalability, accuracy and power consumption (battery changes reduced).

5.1.4 UC-BLS-5 (Equipment Monitoring and Line Visualisation)

At the moment, due to time constraints, the MES files are being manually transmitted to the cloud so, in the future, the same data transfer infrastructure used in UC-BS2 (where files are being automatically sent so the data can be instantaneously shown on the COMPOSITION DSS) could be applied to this use case.

5.1.5 UC-KLE-3 (Scrap Metal and Recyclable Transportation)

As already described before, UC –KLE 3 Scrap Metal and Recyclable Waste Transportation is triggered by full bins at KLEEMANN’s shop-floor. VL53L0X micro-Lidar Time of flight Sensor was used for fill level measurements. The sensor captures raw measurements of distance of the waste heap from the deployment point. The STM32L053c8t6 low power microcontroller controls the sensor and the communication. The microcontroller-sensor communication is carried out through an I2C bus that can serve multiple sensors. The microcontroller also checks for faulty measurements, repeats the measurement process again, and if the measurement is faulty sends an error flag. The wireless communication is carried out via the sx1272mbas LoRa Module for STM. More information about the fill level sensor deployment and the analysis of data can be found in deliverable *D3.5 Computational Modelling, Simulation and Prediction of Production II*.

5.2 Human Machine Interfaces (HMIs)

Evaluation sessions were conducted on both shop floors. The evaluations were planned from both FIT and ATL and the most suitable personnel participated on the sessions.

The sessions included personal interviews with the personnel, live testing and use of the applications and finally the results were obtained by using a blended questionnaire based on the combination of the user-centric approach and the ECOGRAI method (Bangor et al, 2009) (Brooke, 1996) (Doumeingts et al, 1995) (Hassenzahl, 2001) (ISO1, 2006) (ISO2, 2010) (Vamvalis, 2017). A document was created for the evaluation sessions that contained the previous situation on the shop floor and what should be achieved by using the COMPOSITION project (see sections 5.2.1 and 5.2.2). There also are the steps and the instructions the user should follow to complete the tasks. Further details will be included in *D8.8 Final evaluation of the COMPOSITION IIMS platform,* due in M36.

The evaluation focused on the HMIs of the INTRA-factory use cases for predictive maintenance. Most of the HMIs for BSL-2 Predictive maintenance and KLE-1 Maintenance decision support, contain the same elements. Therefore, the same evaluation was conducted on both shop floors and lead to similar consistent results. Some changes to the design and interaction of visual elements were received that should be followed through all COMPOSITION HMIs. The main HMI was well received by participants of both partners, providing most of the necessary information. Regarding the Rule Engine HMI, there were observations that should be redesigned to follow the common design for the COMPOSITION project.

More details about the current state of the HMIs and what changes will be made based on the evaluation, can be found in *D5.5 - Human-Machine-Interfaces for direct interaction with the factory environments I*.

5.2.1 UC BSL-2 Predictive Maintenance

<u>Pre-COMPOSITION State, AS IS</u>

The maintenance procedures on Boston Scientific Ltd shop floor follow the logic of scheduled maintenance processes to prevent failures. When a failure occurs on one of the machines, the operator logs it on the maintenance monitoring system and declares a malfunction. Afterwards, the maintenance team checks the failure and decides which team or which person specifically will go and solve it, following specific steps during maintenance procedure.

In the operational environment of Boston Scientific Ltd at Clonmel, malfunctions with the ovens and specifically with ovens’ fans do not occur often, just from time to time. The operation of the fans at non- optimal operational conditions gradually leads to malfunctions. If this fact remains unnoticed, the machine would deteriorate over time, thus leading to failures.

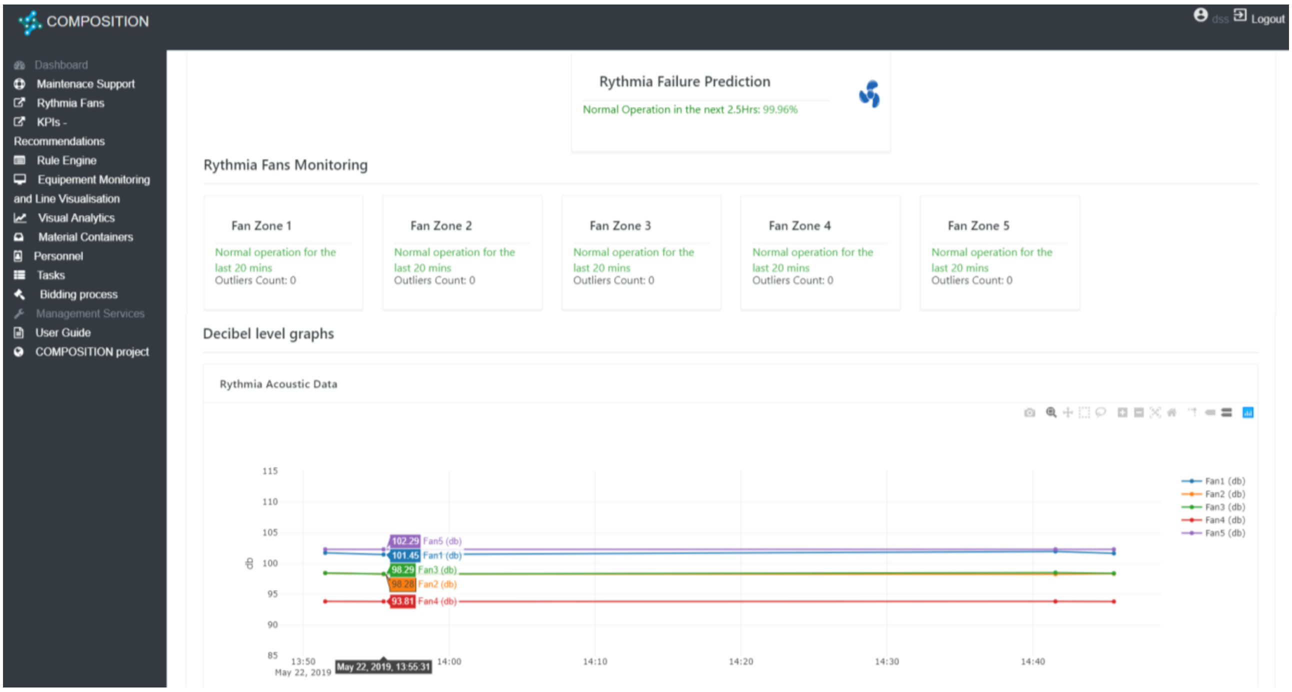
Higher than normal temperatures may also cause malfunctions and breakdowns on the machines. Operators understand, by experience, when a machine appears to have a problem caused by higher temperatures, lack or variation of power etc. The following parameters are being measured and logged: temperature, pressure, power consumption.

Implementation of COMPOSITION Solution

The COMPOSITION component Maintenance Decision Support System (DSS) is a complete solution that improves maintenance delivery on the shop floor and allows predictive actions. Sensors are installed in the machines to monitor their operation. Data is sent to the COMPOSITION Decision Support System where it is visualised and analysed to provide predictions and suggestions the maintenance manager. The DSS operation is near real-time and provides information about the state of the machines. Using the COMPOSITION solution, managers save time in maintenance procedures, because failures can be predicted and the maintenance plan can be accordingly adjusted. Also, historical data from the shop floor is used in the Deep Learning Toolkit (DLT) where a prediction of failure over the next 200 minutes (almost two and a half hours) is calculated.

The aforementioned process is necessary to lead to what the user sees: alarms and suggestions for actions when there is a high probability to have an operation status outside standard operational limits. Based on pre-defined rules, a suggestion or a warning or a notification is sent to the suitable actor. Time is critical in maintenance procedures. The use of COMPOSITION DSS enables predictive maintenance instead of corrective maintenance or time-based planned maintenance and prevents major failures.

The rule engine is used by the maintenance manager to define the rules according to operational procedures, taking advantage of the already existing historical data and his/her experience. The rules include different states and measured parameters. Based on previous operation, the thresholds of the states are defined, as well as the exact parameters and conditions that trigger a transition. The maintenance manager defines the notifications or warnings of each state. Finally, the maintenance manager or the technician supervisor can use the notifications mechanism to send notifications to the suitable actors. All the above can be parametrised whenever needed.



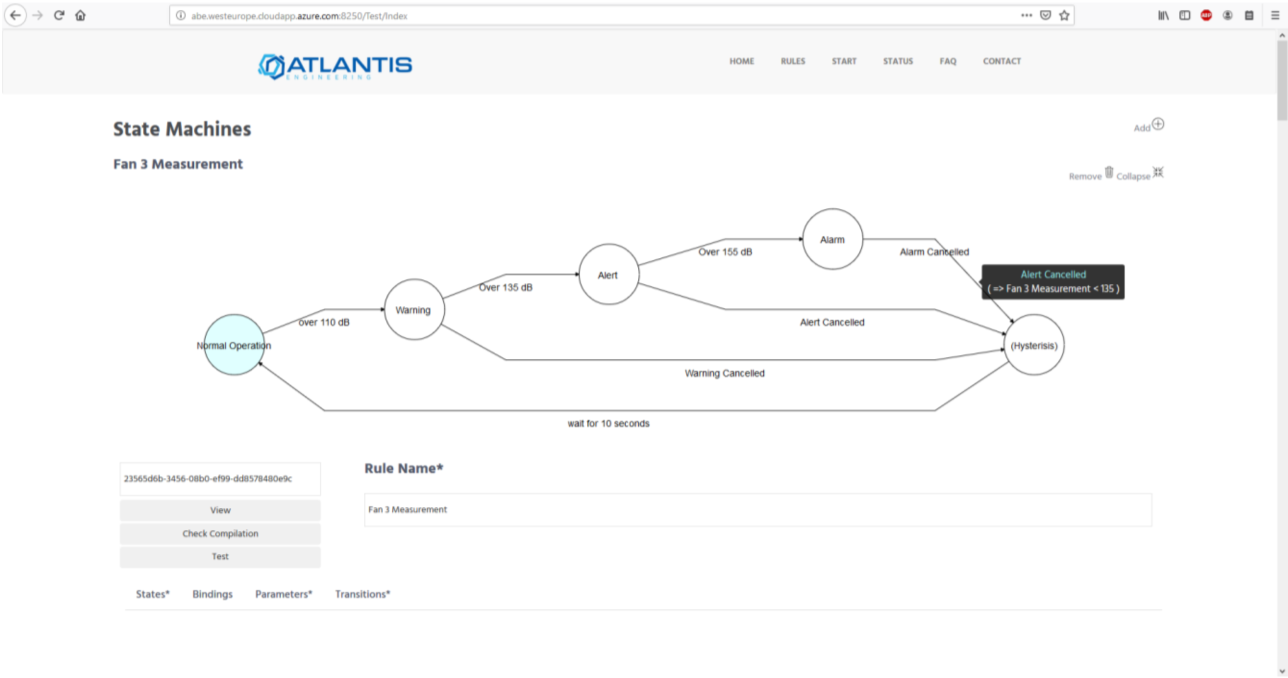


Figure 17 - DSS and Rule Engine for UC-BLS-2

5.2.2 UC KLE-1 Maintenance Decision Support

Pre-COMPOSITION State, AS IS

The maintenance procedures on the KLEEMANN shop floor follow the typical organization of the maintenance department of big manufacturing shop floors. The procedure includes five different actors from workers to managers, with a hierarchical structure in the maintenance procedure.

When a failure is observed by the workers on the machines, it is reported to an area supervisor and they in return create an entry to the CMMS. Afterwards, the information about this failure reaches the maintenance manager who prioritises it. If their understanding of the criticality of the failure mode is high, then the process technician is informed to provide all the necessary assets and maintenance procedures for the maintenance. Then the technician supervisor is responsible to send the suitable technicians to repair the failure. The current state causes a load to the maintenance manager and a backlog for maintenance tasks.

Implementation of COMPOSITION Solution

The COMPOSITION solution of Maintenance Decision Support System (DSS) is a complete solution that improves maintenance delivery on the shop floor and allows predictive actions. Sensors are installed in the machines to monitor their operation. Data is sent to the COMPOSITION Decision Support System where it is visualised and analysed to provide predictions and suggestions the maintenance manager. The DSS operation is near real-time and provides information about the state of the machines. Using the COMPOSITION solution, managers save time in maintenance procedures, because failures can be predicted and the maintenance plan can be accordingly adjusted. Also, historical data from the shop floor is used in the Simulation and Forecasting Toolkit (SFT) to predict a probability of failure for the three detected failure modes (mechanical, electrical and hydraulic). The probabilities are fed to the DSS to fill rules' parameters with trained thresholds and state values.

The aforementioned process is necessary in order to lead to what the user sees: alarms and suggestions for actions when an operation outside standard operational limits has a high probability of occurring. Based on pre-defined rules, a suggestion or a warning or a notification is sent to the suitable actor. Time is critical in maintenance procedures. The use of COMPOSITION DSS enables preventive maintenance instead of corrective maintenance or time-based planned maintenance and prevents major failures.

The rule engine is used by the maintenance manager to define the rules according to operational procedures, taking advantage of the already existing historical data and his/her experience. The rules include different states and measured parameters. Based on previous operation, the thresholds of the states are defined, as well as the exact parameters and conditions that trigger a transition. The maintenance manager defines the notifications or warnings of each state. Finally, the maintenance manager or the technician supervisor can use the notifications mechanism to send notifications to the suitable actors.

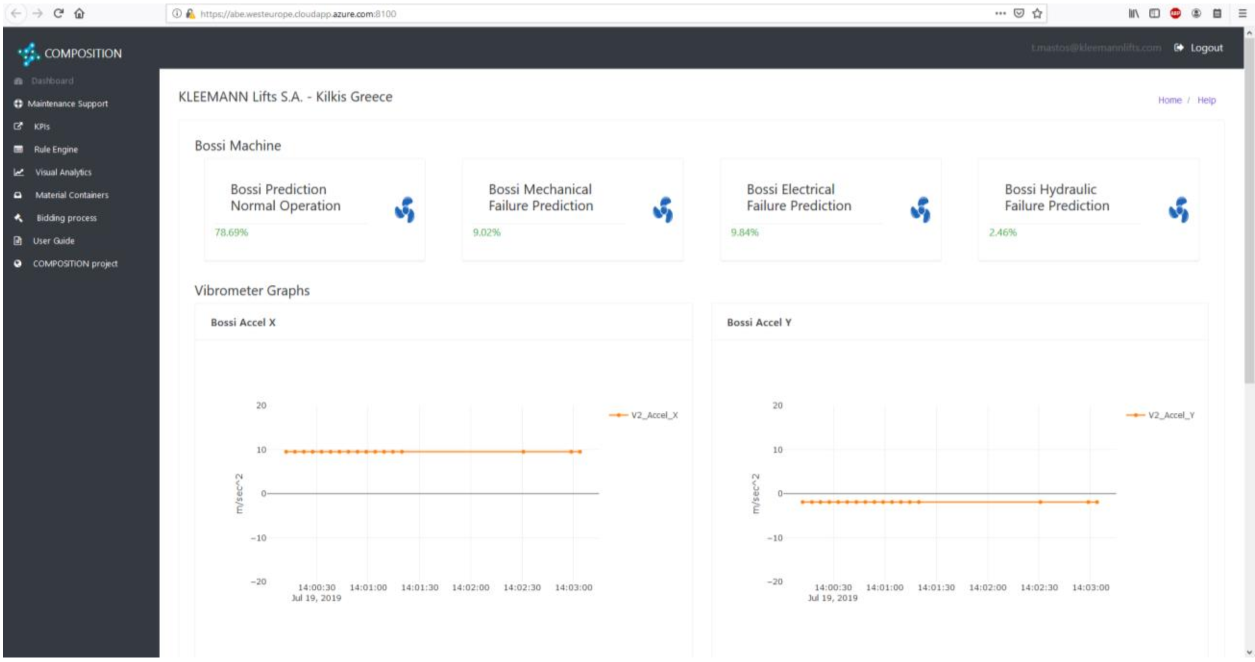


Figure 18 - Dashboard for UC-KLE-1

Besides the Probability of Faults based on historical data, a solution based on real time vibration sensor's data is available as well. In this case, a Machine Vibration Diagnosis Profile algorithm has been implemented in SFT in order to discover in real-time abnormal operation of motors from BOSSI polishing machine. Finally, SFT propagates its output to Visual Analytics tool for visualization and monitoring. Moreover, an event in a situation of abnormal behaviour is available in DFM in order to trigger a notification coming from DSS. An instance of VA tool for vibration profile is available in next figure:

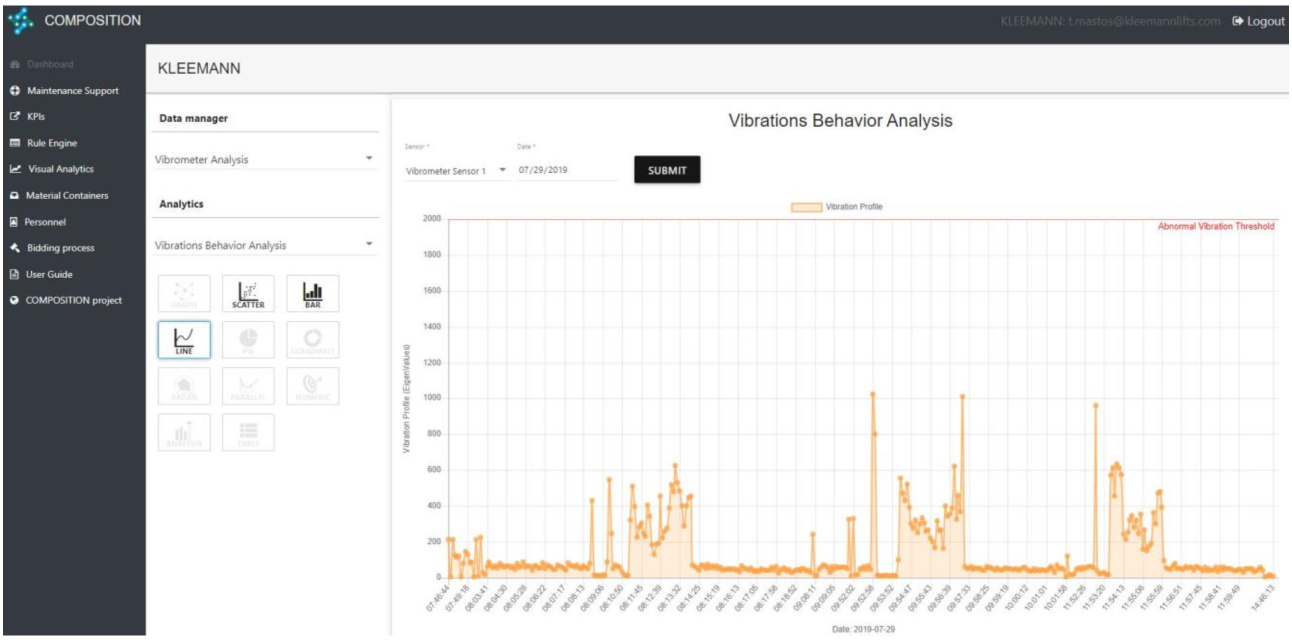


Figure 19 - Visual Analytic for Vibrations Behaviour in UC-KLE-1

5.2.3 UC-BSL-3 (Asset Tracking)

Pre-COMPOSITION State, AS IS

Before COMPOSITION, there was no standardised process targeting this problem, employees had to search laboriously and manually for lost components/equipment, which were required for validation or calibration, with some not being found for long periods or at all. On average, 25% of the equipment due for calibration misses the deadline, because it was missing at the time due to misplacement.

Implementation of COMPOSITION Solution

With COMPOSITION implemented, the employee only has to log into the COMPOSITION dashboard, which has a link to AirFinder, and the equipment is displayed on a live visualisation screen (Figure 20). With this solution, the time taken to find the equipment has greatly decreased.

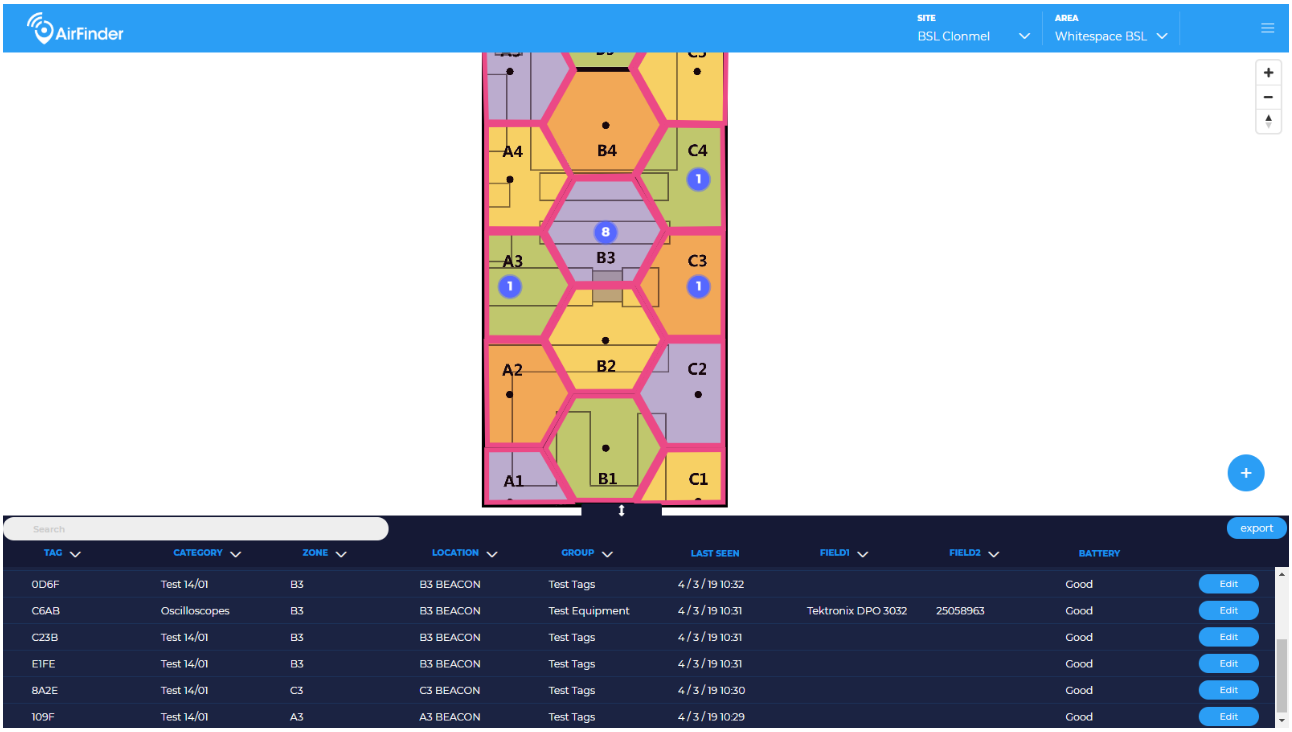


Figure 20 - Dashboard for UC-BSL-5

5.2.4 UC-BSL-5 (Equipment Monitoring and Line Visualisation)

Pre-COMPOSITION State, AS IS

Before COMPOSITION there was no automatic record of how long equipment is in alarm state or is down and there was no reliable way to track equipment up-/downtime and the production hours lost due to equipment issues. All the information needs to be obtained manually which takes a lot of time and effort.

Equipment issues are reported orally by the product builders to the technicians. Updates on the status of equipment are completed by e-mail or in person where it is hard to keep track of, which results in relevant personnel (PB, Technicians, Supervisors, Engineers, Managers) not being correctly informed.

In the current state, production hours are lost due to a delay in informing technician and engineers.

Implementation of COMPOSITION Solution

With COMPOSITION implemented the information is clearly displayed on the DSS as shown on Figure 21.

Unfortunately, due time constraints automated data transfer is not currently in place. However, with every manual data transfer, the system allows a full line visualisation, where it will be easier to see which equipment is free and can be optimised, or where a bottleneck is originating.

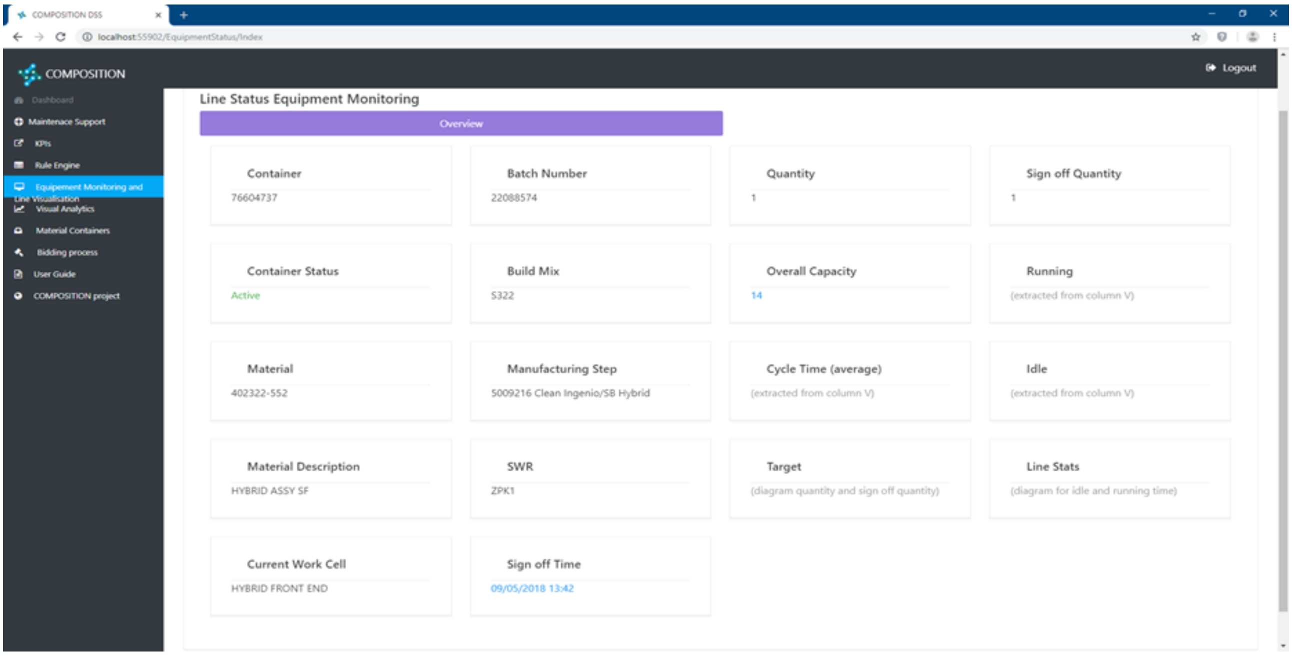


Figure 21 - Dashboard for UC-BLS-5

5.2.5 UC-KLE-3 (Scrap Metal and Recyclable Transportation)

Pre-COMPOSITION State, AS IS

Scrap metal and recyclable waste are produced and collected in bins inside the shop-floor. When the bins are full, they are transported to outdoor containers at KLEEMANN's premises. Forklift drivers are responsible for collecting the scrap metal and recyclable waste when the bins are full. The drivers perform manual observations to the indoor bins to check the fill levels. Every day, forklift drivers check and pick up tens of bins. This process increases costs due to the time lost in checking bins that are already full and may sometimes cause congestion within the factory or delays in other tasks. Hence, the removal of the scrap metal and the recyclable waste is critical due to the limited availability of the bins and the congestion that maybe caused.

Implementation of COMPOSITION Solution

The COMPOSITION solution for scrap metal and recyclable waste transportation provides early and automated detection of scrap metal and recyclable waste fill levels in order to empty the bins before they get full. The solution also offers a notification for the shortest/optimal route to the personnel, which reduces the possibility of congestion. Using the COMPOSITION solution, forklift drivers save time in waste collection procedures and ultimately reduce costs. Figure 22 shows the dashboard and fill levels for UC-KLE-3. An application is also developed for mobile phones (Figure 23).

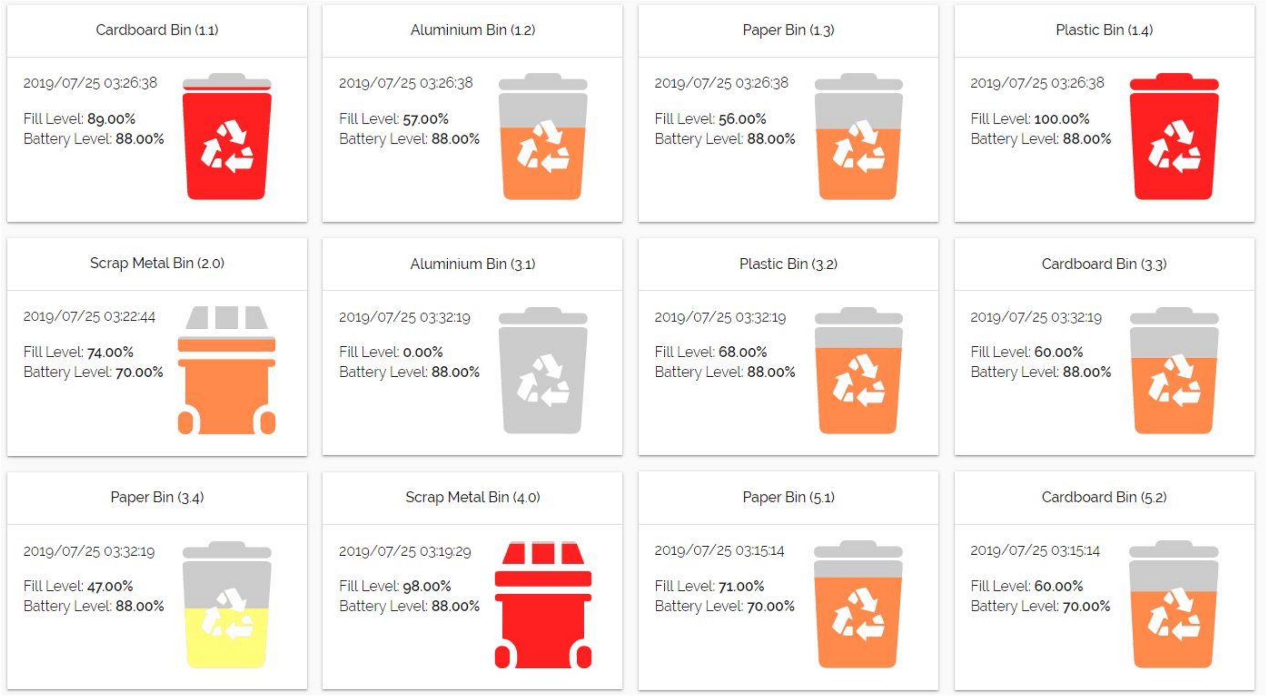


Figure 22 - Dashboard for UC-KLE-3

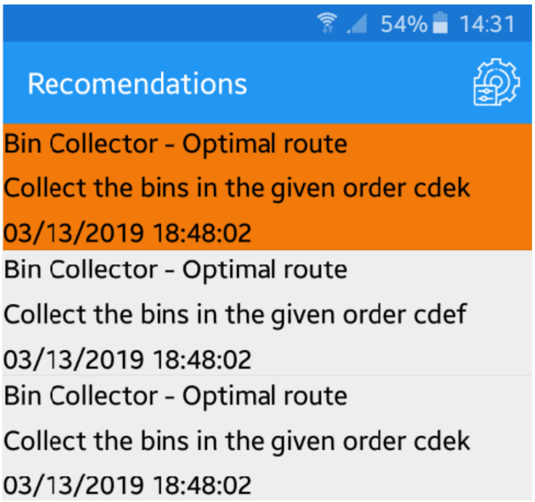


Figure 23 - UC-KLE-3 Bin Collector - Optimal route application

5.3 Value chain risks (use cases and technology)

A risk assessment was performed for all use cases (Table 13) and technology (Table 14) being used on the Value Chain Pilot. The tables bellow contain the findings of that same assessment, as well as measurements to manage/mitigate the risk that might arise from the pilot. The scoring on these tables was based on the risk matrix that can be found on this document's Annex A - Risk Assessment Matrix

5.3.1 Use case risk assessment

Table 13 - Use case risk assessment

Use case	Associated Risk(s)	Severity	Probability	Risk Score	Method(s) to Manage/Mitigate the Risk
Predictive Maintenance (UC-BSL-2)	1. Interfere with the normal production of the reflow oven 2. Interfere with the product in the oven 3. Send the wrong/unsynchronized data from the sensor/reflow oven 4. Send corrupted data from the sensor/reflow oven	1. Critical 2. Catastrophic 3. Critical 4. Critical	1. Low 2. Low 3. Medium 4. Low	1. Medium (6) 2. High (10) 3. High (8) 4. High (9)	1. Keep data on separate PC and make sure everyone is aware that the sensors are in the oven 2. Keep sensors away from product in the oven. Ensure a fault with the sensors won't result in scrap/damage to the material in the oven 3. Have the data collection checked regularly 4. Have the data check regularly for corrupted parts
Equipment Monitoring and Line Visualization (UC-BSL-5)	1. Send wrong data from the equipment 2. Unavailable data	1. Marginal 2. Marginal	1. Medium 2. Medium	1. Medium (5) 2. Medium (5)	1. Have the data collection checked regularly 2. Check regularly for data availability and provide data with a different way when it is not available.
Component Tracking (UC-BSL-3)	1. Send the wrong information/location of equipment 2. Interfere with normal production on the factory floor	1. Marginal 2. Critical	1. Medium 2. Low	1. Medium (5) 2. Medium (6)	1. Have the data collection checked regularly 2. Keep tracking system separate from any systems on the factory floor until the system is

					shown to have no affect
Installation of vibrometer outside the polishing machine (UC-KLE-1)	1. Damage Polishing Machine 2. Interrupt production programme 3. Injury to installers (technicians) 4. Data not available	1. Critical 2. Marginal 3. Critical 4. Critical	1. Low 2. Low 3. Low 4. Low	1. Medium (6) 2. Medium (4) 3. Medium (6) 4. Medium (6)	1. Educate participants regarding the sensor activity. The vibrometer is installed outside the polishing machine, so no interventions will be required. 2. Contact production supervisor and manager to arrange a specific time for installation that does not interrupt the production. 3. Ensure the machine is not working. Ensure and inspect that all work is performed based on company's health and safety policy and procedures. 4. Not connected to the machine power line. Check power. Not connected to the Wi Fi network. Reset Wi Fi adapters for vibrometer and router. There is also the possibility that the machine is

					offline and there in no available data
Installation of fill level sensors (UC -KLE-3)	1. Damage sensor form other machines 2. Wrong data provided due to misuse	1. Critical 2. Marginal	1. High 2. Low	1. High (9) 2. Medium (4)	1. The sensor can be damaged from bigger equipment of the shop floor. Build cases to withstand the impacts and install the sensor outside of the polishing machine box. 2. Train users to correctly fill the bins.

5.3.2 Technology risk assessment

Table 14 - Technology risk assessment

Use Case	Associated Risk(s)	Severity	Probability	Risk Score	Method(s) to Manage/Mitigate the Risk
COMPOSITION Asset Tracking UC-BSL-3	Airfinder cloud-based solution may not meet to BSL network security requirements and therefor system will be unable to function.	Critical	Medium	High (8)	1. TNI working with Asset tracking vendor and BSL on network security issues to resolve. 2. There is the possibility that vendor can supply a local version of software that does not need network connection 3. Alternative UWB solution has been assessed and could be introduced at the expense of some technical requirements

COMPOSITION Asset Tracking UC-BSL-3	Radio emissions do not meet BSLs requirements on the manufacturing floor	Critical	Low	Medium (6)	1. Procure units that meet FCC and ETSI regulations 2. Investigate alternative technologies
COMPOSITION Asset Tracking UC-BSL-3	Asset tracking does not meet accuracy requirements	Critical	Low	Medium (6)	1. Introduce UWB technology (bear in mind this does not meet battery / size requirements) 2. Increase density of anchors
COMPOSITION Asset Tracking UC-BSL-3	Interfere with shop floor infrastructure (metal beams, constructions etc)	Critical	High	Medium (8)	1. Try to eliminate the risk by adapting to the limitations on the shop floor.
COMPOSITION Predictive Maintenance UC-BSL-2	1.Acoustic sensors failure due to high temperature environment they are subject to. 2. Accoustic sensors data analysis incorrect	1.Marginal 2.Marginal	1.Low 2.Low	1.Medium (4) 2.Medium (4)	1. Re-position sensors to a more benign environment. 2. Replace with embedded solution that has better robustness 3. Analyse again incorporating all available input
COMPOSITION Shop Floor Connectivity / BMS UC-KLE all UC-BSL-all	1. Data is not available due to connectivity problems 2. Data from shop-floor is incomplete 3. Broker is down 4. Sensors are not working or get damaged due to environmental factors	1. Critical 2. Critical 3. Critical 4. Critical	1. Medium 2. Low 3. Medium 4. Medium	1. High (8) 2. Medium (6) 3. High (8) 4. High (8)	1. Connectivity must be constantly monitored, notifications must be sent in case of downservice 2. An initial trial phase is performed to test the robustness of the system 3. Broker connectivity must be monitored 4. Cases have been created to protect sensors. Sensors are tested in lab and after that they deployed to the pilots'

					sites for further testing before the permanent installation.
COMPOSITION data persistence UC-KLE-all UC-BSL-all	Storage queries request excessive amount of data with a single call	Critical	High	High (9)	Queries results must be limited by the data persistence component
COMPOSITION Security Framework All use cases	1. Unauthorized access (malicious or accidental) 2. Misuse of information (or privilege) by an authorized user 3. Data leakage or unintentional exposure of information 4. Loss of data 5. Disruption of service or productivity	1.Critical 2.Critical 3.Critical 4.Critical 5.Catastrophic	1. Low 2. Low 3. Low 4. Low 5. Low	1.Medium (6) 2.Medium (6) 3.Medium (6) 4.Medium (6) 5.High (10)	1. COMPOSITION Security Framework provides strong authorization mechanisms based on EPICA 2. Continuous learning about the data and information management 3. Authentication and authorization management using Keycloak and EPICA 4. Data replication policies 5. Distributed architecture with backup instances running
IoT Learning Agent UC-BSL-2	1.The agent does not process the data and delivers to DLT and front-ends 2.The agent do not forward the data	1.Marginal 2.Marginal	1.Medium 2.Medium	1.Medium (5) 2.Medium (5)	1. The deployment of several instances of the same service will allow the instant recovery in case one fails 2. Same as (1). Additionally, we have secondary systems that could take this task in case the LA fails.

Battery life problems for fill level sensors	1. The sensors are frequently running out of battery and the worker have to change the battery very often	1.Marginal	1.Low	1.Medium	1. Low power friendliness of selected sensors was taken into account. Furthermore, LoRa LPWAN was selected as it was the most suitable for use case needs due to “lightweightness” and low power needs
Errors in fill level measurement for UC-KLE-3	1. Distance sensors, as well as every sensor on market, have a small margin of error. In particular, the surface of the scrap metal may reflect the light on various directions resulting in invalid ranging measurements below 50% in the scrap metal bins	1.Marginal	1.Low	1.Medium	1. The sensor raises a specific error informing the UI that the return signal is too low to give enough confidence on the distance measured so the UI is not updated for this measurement in order to avoid user’s confusion. Moreover, filtering techniques are also applied in both device and software level. Besides that, as the notifications are triggered over 80% of fill level and the described risk is faced under 50%, the problem does not presented.

Visualizations UC-KLE-1	1. The visualizations of vibrations of Bossi machines do not effectively inform about possible failures	1.Marginal	1.Medium	1.Medium	1. Besides the DSS visualization of vibrations, an advanced visual analytic has added on IIMS. It displays the behaviour of Bossi motors based on vibrations alongside with a threshold. As soon as the visualized line passes the threshold, the abnormal activity is visible to the user.
COMPOSITION cloud Servers UC-KLE-all UC-BSL-all	1. Servers are unreachable due to technical issues 2. Servers are unreachable for scheduled maintenance 3. Data is lost due to server failure 4. Data is stolen due to security breach	1.Critical 2.Marginal 3.Critical 4.Critical	1.Low 2.Medium 3.Medium 4.Low	1.Medium (6) 2.Medium (5) 3.High (8) 4.Medium (6)	1. Provide replica servers and load balancers to avoid single point of failure. 2. Inform all stakeholders about scheduled updates, possible schedule updates during off-peak hours to minimize the operational effects. 3. Provide offshore replicas of persistent data. 4. Utilize state of the art security mechanisms, deploy security patches as soon as they are made available, adopt common

					security practices in all aspects of the system from infrastructure to end-user services.

5.4 Assessment of use cases – Simulation and Reality

The deployments for condition monitoring of the fans in the reflow ovens and the asset tracking system deployed are prototypes to enable proof of concept. The predictive maintenance systems are a bespoke design using Commercial Off The Shelf components (COTS). The asset tracking system utilises a commercially available system from Link Labs known as Airfinder.

5.4.1 UC-BSL-2 (Predictive Maintenance)

An example of the type of system that can be introduced for a large-scale deployment is described below. In this system the architecture is stripped down to the necessary components:

1. Acoustic Sensor to measure the sound (within acoustic sensor box in diagram)
2. Ultra-Low Power microprocessor using M0 or M4 core (within acoustic sensor box in diagram)
3. Ultra-Low Power radio IC, probably BLE protocol (within acoustic sensor box in diagram)
4. Battery with associated Power Management (within acoustic sensor box in diagram)
5. Energy Harvester to scavenge power to extend battery life to reduce maintenance. In the example below, Thermal harvesting is used.

These units could be made very small (30 x 30 x 20mm) and attach to the oven via magnets.

The diagram below (Figure 24) shows what a configuration looks like. As one can see all cabling is removed, processing is done within the sensor unit so no WAV files are transmitted and data is brought back to the PC using an COTS dongle. Note that other protocols could be used.

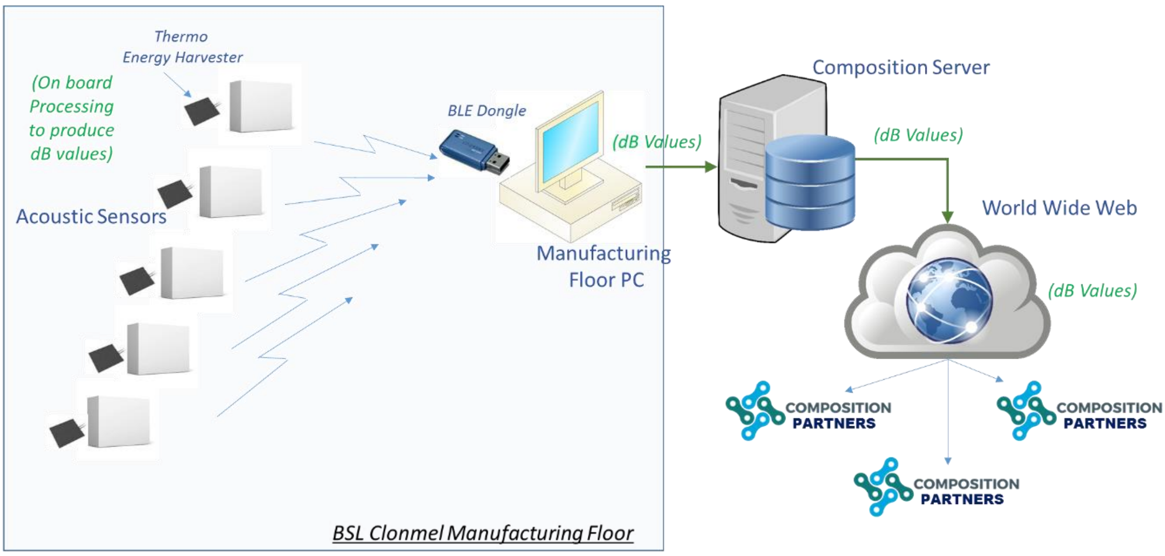


Figure 24 - Diagram of future implementation

5.4.2 UC-KLE-1 (Maintenance Decision Support)

As a pilot partner KLEEMANN evaluated the status and operation of sensors based on on-site observations. It should be mentioned that since the installation of the vibrometers, no failure has occurred. Hence, no failure can be connected to the notification sent from the sensors. However, the threshold of abnormal operation was reached several times (Figure 25), but this was due to the way the piston rolls on the rails and "hits" the absorbers of the BOSSI machine, and not due to failures. KLEEMANN is in the process of vibration monitoring and combining it with the machine's real failures and operator's experience. Overall, the vibration sensors provide accurate measures.

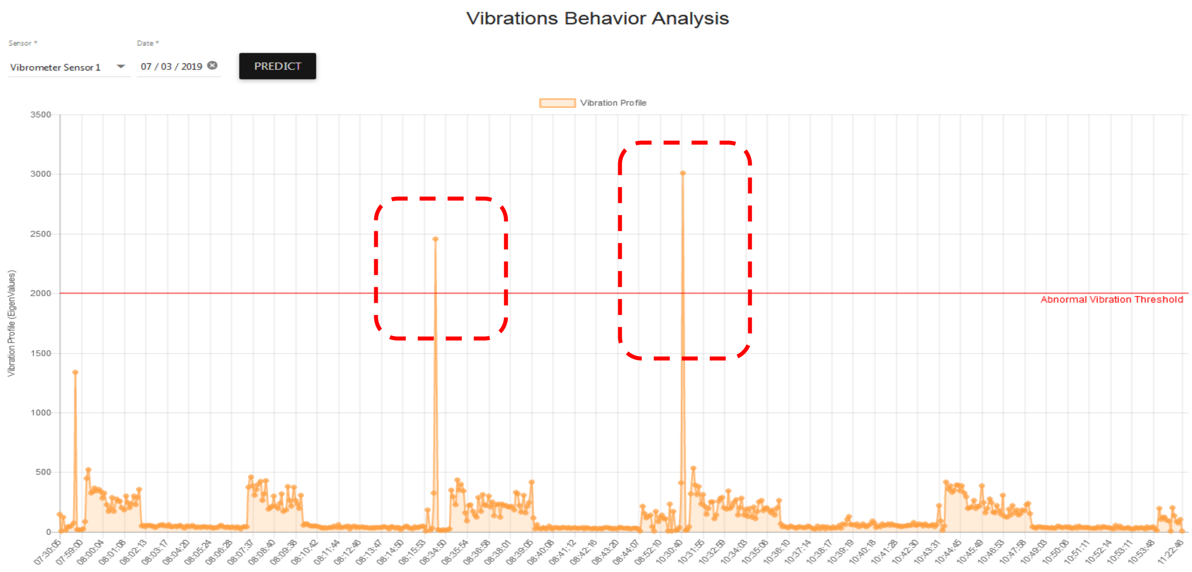


Figure 25 - Abnormal Vibration Threshold

5.4.3 UC-BSL-3 (Asset Tracking)

Although there are many technologies available commercially the application space is very broad and usually demands a bespoke solution. In this case there are no COTS that meet the requirements in BSL. This would require several developments for a system to operate on the production floor.

There are opportunities to incorporate Energy Harvesting techniques in the BLE readers to reduce battery replacements. Some applications require higher accuracy and this would require adoption of UWB or phase difference of arrival systems. These would have to undergo significant development to reduce power consumption to a level acceptable for yearly or longer battery replacements.

For the COMPOSITION project the plan is to remain with the BLE system and look at reducing tag size and extending battery life on the readers by use of energy harvesting techniques

5.4.4 UC-KLE-3 (Scrap Metal and Recyclable Waste Transportation)

The same procedure is followed in this use-case too. A comparison between on-site observations and sensor fill level data is performed. Some examples are given below for recyclable waste bins and scrap metal bins (Table 15). As shown, the differences between on-site estimation and sensor fill level measure range from 0% to 10%, which demonstrates the accuracy of fill level sensors measurements,

Table 15 - UC-KLE-3 sensor assessment

Date	Time	Photo	On-site estimated fill level	Sensor fill level	Difference
06/07/2018	10:57		110%	110%	0%
06/07/2018	11:00		60%	58%	2%
11/07/2018	11:33		95%	93%	2%
19/07/2018	11.05		50%	49%	1%

20/09/2018	12:39		50%	55%	5%
20/09/2018 (S4)	12:50		90%	100%	10%
20/09/2018 (S2)	12:52		30%	38%	8%
20/09/2018 (S3)	12:56		25%	28%	3%

20/09/2018 (S1)	13:00		65%	63%	2%
28/09/2018 (S1)	13:00		48%	58%	10%
28/09/2018 (S2)	13:02		45%	52%	7%
28/09/2018 (S3)	13:05		0%	error	-
28/09/2018 (S4)	13:10		80%	87%	7%

28/09/2018	13:15		0%	0%	0%
08/11/2018	13:30		61%	62%	1%

6 Conclusion

All the presented use cases; UC-BSL-2, UC-BSL-3, UC-KLE-1, UC-BSL-5 and UC-KLE-3, where successful in terms of implementation and deployment.

Data from UC-BSL-2 is being collected and transmitted in real-time to the COMPOSITION cloud, with several datasets being identified and presented to the Deep Learning Toolkit for the training of its artificial neural networks in order to achieve an accurate prediction. The original existing information from the equipment is now extended with the acoustic data, thus generating a comprehensive dataset that allows a suitable mapping of this use case's gathered information. Regarding UC-KLE-1, KLE is currently in the process of defining thresholds for the failure notifications in the *BOSSI* polishing machine.

Due to the cloud nature of the COMPOSITION project, instead of deploying the BMS on a physical server, this system was deployed as a cloud service collecting data through direct MQTT connection for the KLE pilot and sftp for the BSL pilot. Due to internal security reasons, instead of live data, the collected information is transmitted every 5 minutes to the BMS server and fed using a software script.

Overall, the deployed systems combine the technical work that was developed in the technical WPs that are relevant for the value chain part of COMPOSITION, i.e. WP3 and WP5. The different components were integrated in the scope of WP7.

A list of KPI's was identified for all the use cases, based on the incoming data from each partner and the failure definitions from each equipment. A Human Machine interface was designed and currently allows the visualization of each partner's KPI's. Evaluation sessions on both partners were conducted and the findings from that evaluation where used for the design of the final iteration of the HMI. Comparing the use-cases with original KPIs from the Description of Action almost all the use-cases met or exceeded the target percentage.

In Boston Scientific, UC-BSL-2 Predictive Maintenance gave promising results, meeting or exceeding the targets on the relevant KPIs. UC-BSL-3 Asset Tracking showed great improvements in terms of cost savings and reduction in lost time looking for equipment. Although UC-BSL-5 Equipment Monitoring and Line Visualisation was not running long enough to show significant results for some of the KPIs, with full line visualisation, there will be an overall reduction in down-time.

At KLEEMANN, UC-KLE-1 Maintenance Decision Support met most of its targets, with cost savings for process monitoring and a reduction in down-time. For UC-KLE-3 Scrap Metal and Recyclable Waste Transportation, the forklift's fuel consumption and cost were reduced by 4%, with further improvement expected if the system is expanded in the future.

Overall, the technology being used on the value chain pilot (both at BSL and KLE) is well accepted. BSL believes that, for both their use cases, there is still margin for improvement, especially if the pilot is scaled to the point of being implemented and deployed across the whole site. KLE is satisfied with the increase in measurement frequency (allowing the capture of more data points) and the new sensor sensitivity level.

The risk assessment revealed certain low to medium risk probabilities, however, the methods to manage/mitigate these risks were identified and are already in place.

These results show significant potential to improve collaborative manufacturing conditions in both BSL and KLE. In a future project, BSL and TNI-UCC believe it would be interesting to see power harvesting solutions applied to the acoustic sensors being used for UC-BSL-2 as well as a reduction of the footprint from these sensors inside the oven. For UC-BSL-3, it would also be interesting to develop further work in terms of tag size reduction and battery life extension.

7 List of Figures and Tables

7.1 Figures

7.2 Tables

8 References

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Annex A - Risk Assessment Matrix

		Severity			
		NEGLIGIBLE small/unimportant; not likely to have a major effect on the operation of the event	MARGINAL minimal importance; has an effect on the operation of event but will not affect the event outcome	CRITICAL serious/important; will affect the operation of the event in a negative way	CATASTROPHIC maximum importance; could result in disaster; WILL affect the operation of the event in a negative way
Probability	LOW This risk has rarely been a problem	LOW (**1**)	MEDIUM (**4**)	MEDIUM (**6**)	HIGH (**10**)
	MEDIUM This risk will MOST LIKELY occur at this event	LOW (**2**)	MEDIUM (**5**)	HIGH (**8**)	EXTREME (**11**)
	HIGH This risk WILL occur at this event, possibly multiple times, and has occurred in the past	MEDIUM (**3**)	HIGH (**7**)	HIGH (**9**)	EXTREME (**12**)

Explanation of Risk Ranking		
LOW	MEDIUM	If the consequences to this event/activity are LOW / MEDIUM, your group should be OK to proceed with this event/activity. It is advised that if the activity is MEDIUM, risk mitigation efforts should be made.
HIGH		If the consequences to this event/activity are HIGH, it is advised that you seek additional event planning support.
EXTREME		If the consequences to this event/activity are EXTREME, it is advised that you **do not hold** this event without prior consultation with Risk Management