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D8.5 Value Chain Pilot I

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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 also describes how the COMPOSITION operating system can be implemented in a value 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 under development at BSL and KLE and shows they are successfully being implemented. 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 will be displayed using an HMI specifically designed for the COMPOSITION project. A first evaluation of that interface already took place and its discoveries are already being used to generate the HMI’s next iteration.

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.

With this deliverable, the successful completion of MS13 is verified, with a first iteration of the COMPOSITION platform being effectively deployed and evaluated.

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
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
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 first iteration of the industrial pilot focused on value chain. Several use cases are being 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 same use cases in terms of technology assessment, human machine interfaces (HMIs) and risk analysis. This document will be updated and have its final iteration in “D8.6 Value Chain pilot II” due in M36**.**

3.2 Content and structure of this deliverable

After the initial executive summary and contextualization on section 3, this deliverable starts reporting the Intrafactory Value Chain Centric Pilot demonstrators on section 4, with a description of the two use cases being implemented at BSL (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 this pilot. After the presentation of the risk assessments from both 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 Intrafactory 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.

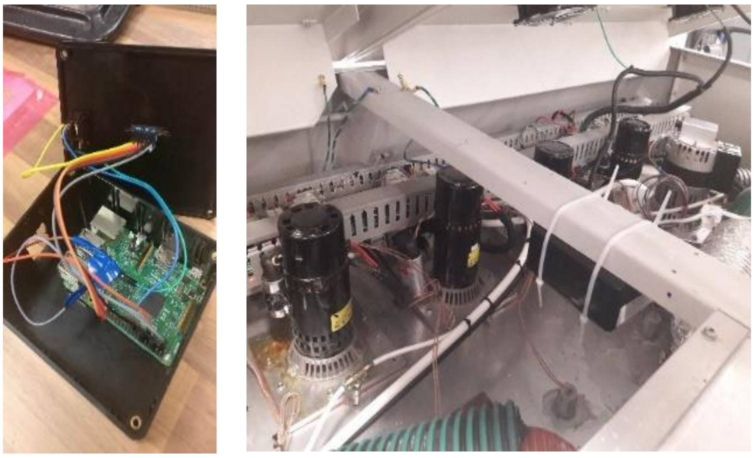

Figure 1 - Set-up inside reflow oven

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 is currently being analysed by the partners to use as 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.

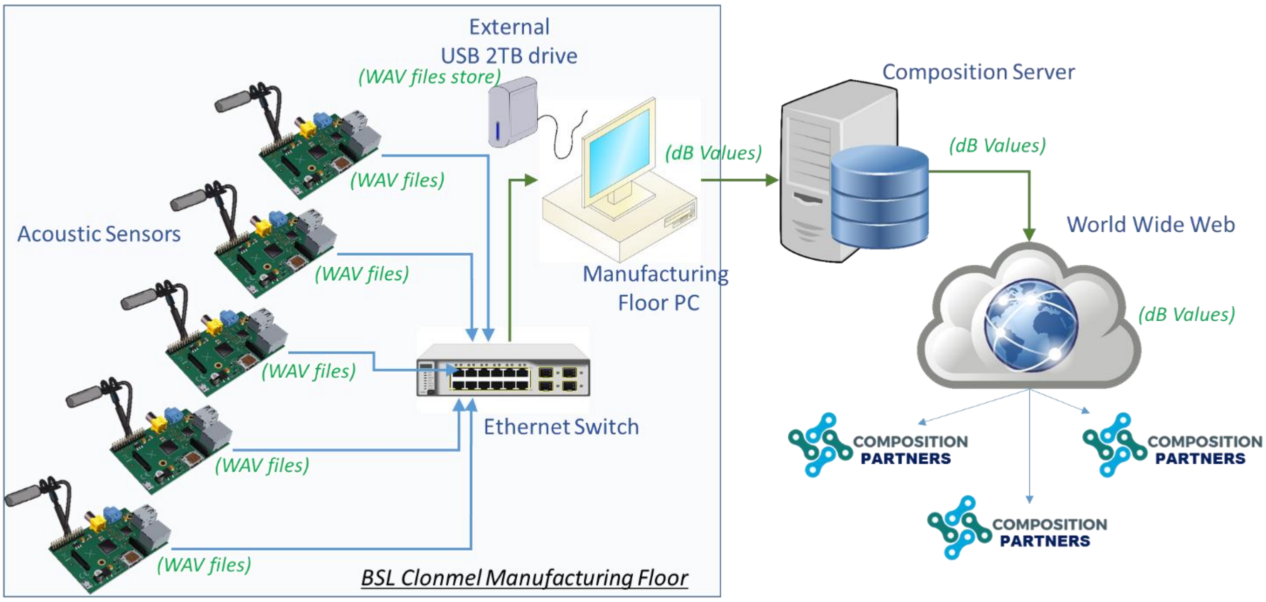

Figure 2 - Overview of the acoustic system

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.

4.1.2 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 is being installed in a prototyping area in BSL. On Figure 3, 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 3 - 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 with the desired locations where the several components of the tracking system will be installed (readers on the ceiling, gateways on the side wall and tags on the components that will be tracked).

The diagram below (Figure 4) 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.

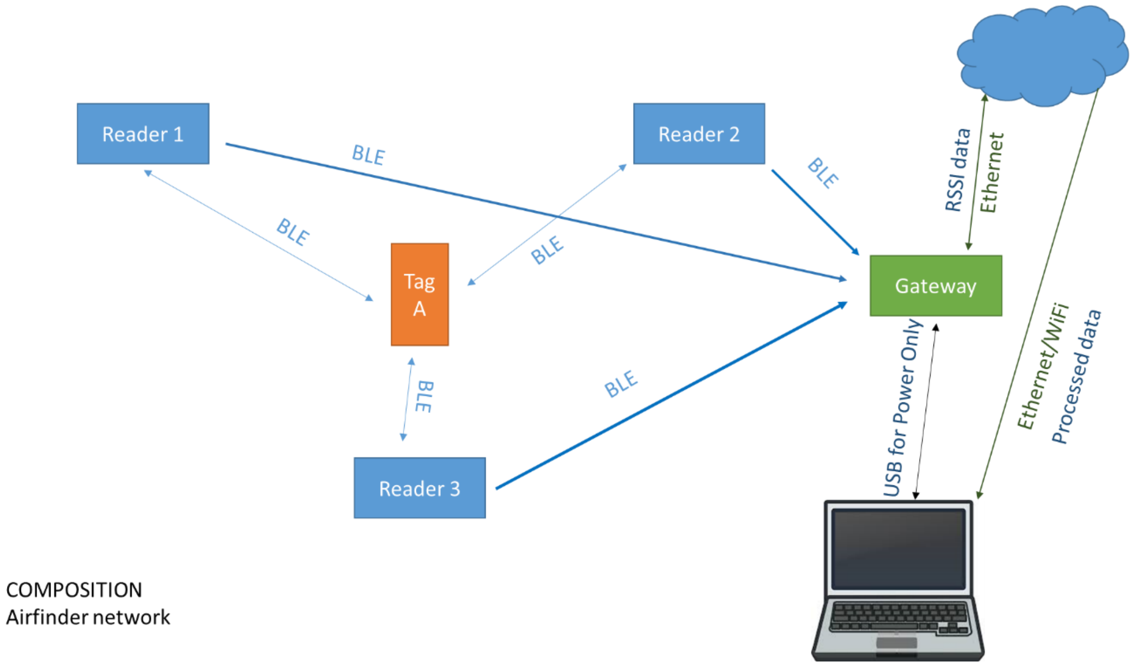

Figure 4 - Diagram of Airfinder’s information flow

4.1.3 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. 590 breakdowns have been recorded in a period of 10 years (2007-2017). 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 inside and outside of the *BOSSI* machine by CERTH. The sensors used in order to capture vibration data are accelerometers. More information about the sensor types can be found in *"D7.6 On site Readiness Assessment of Use Cases based on Existing Sensor Infrastructure I"*.
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

4.1.4 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
Oven sensor	Each blower logs two values: the measured temperature [°C] and the	Textual data structured as a list of records, one per row.	From November 2013 to April 2018

	output power at the solid-state relay of the reflow. Records are sampled every 5 minutes.	Each row is timestamped.	
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.	From November 2013 to April 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)	-

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 3):

Table 3 - 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 will be described on "*D5.4 Continuous Deep Learning Toolkit for real time adaptation II"* at M30.

4.1.5 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 5) and by transferring log files via sftp, with respect to the BSL pilot (Figure 6). Thus, the BMS that processes and forwards the live information is the same instance.

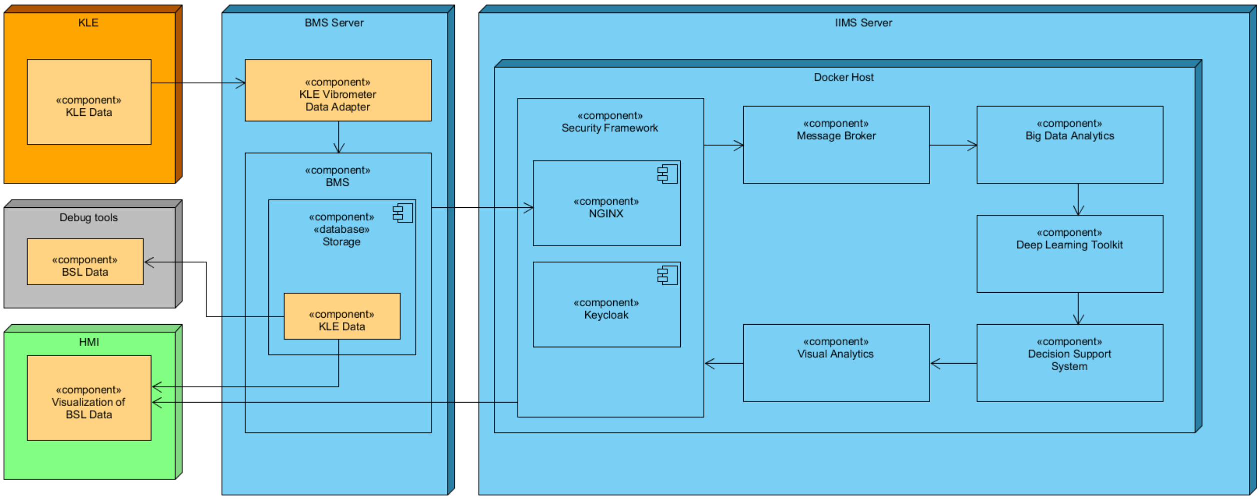

Figure 5 - KLE use cases deployment

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 UC-BSL-2 Predictive Maintenance use case, since it was not possible to get live information from the devices, due to strict security rules of the pilot partner, log files 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.

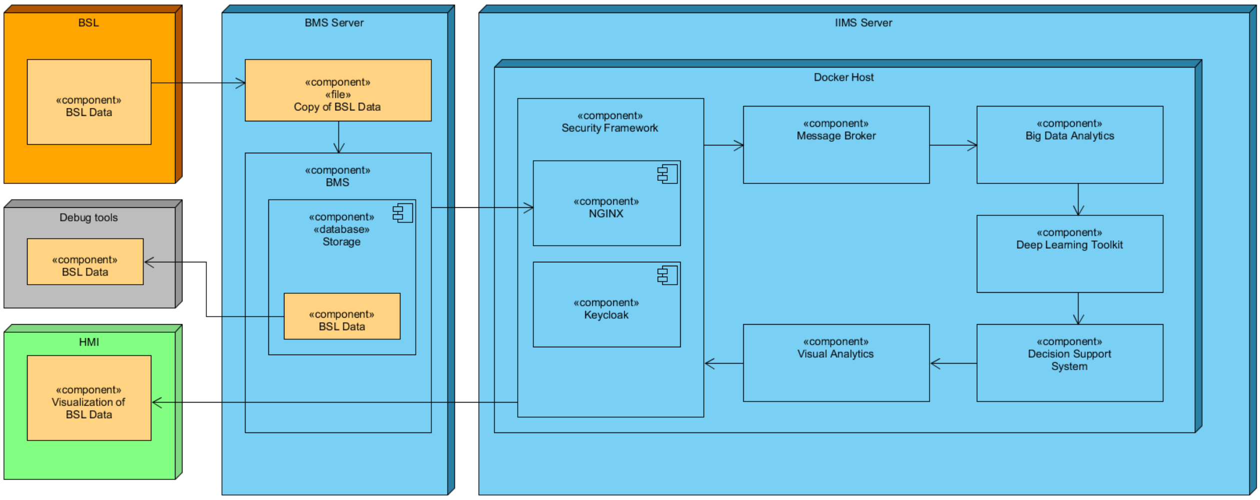

Figure 6 - BSL use cases deployment

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

[1] https://www.breeam.com/

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. It is noted that for each use case the nature of the data and failures are listed, resulting in the suggested KPIs in this initial phase. The KPIs will be revisited in the next round of pilot tests.

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

The suggested KPIs depending on the existing data are:

Suggested KPIs

- Mean Time to Repair, MTTR
- Mean Time Between Failures, MTBF
- Number of Failures counted over a certain period
- Number of alerts over a certain period
- Number of failures depending on types of incoming data
- Number of maintenance tasks over a certain period
- Percentage of failure modes in time

- Possibility of failure depending on the incoming data and the failure modes
- Maintenance Task Durations
- Types of failure modes in a certain period (percentage)

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

The suggested KPIs for the incoming data set and failures are:

Suggested KPIs

- Mean Time Between Failures, MTBF
- Mean Time to Repair, MTTR
- Number of failures over a certain time period
- Number/percentage of alarms/events that were translated into a maintenance task
- Number of events/alarms for the last specific time period detected by the vibration sensor
- Number of alerts and alarms sent from the DSS for the acceleration levels
- Number of events/alarms for the last specific time period detected by the vibration sensor

Figure 7 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 several 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.

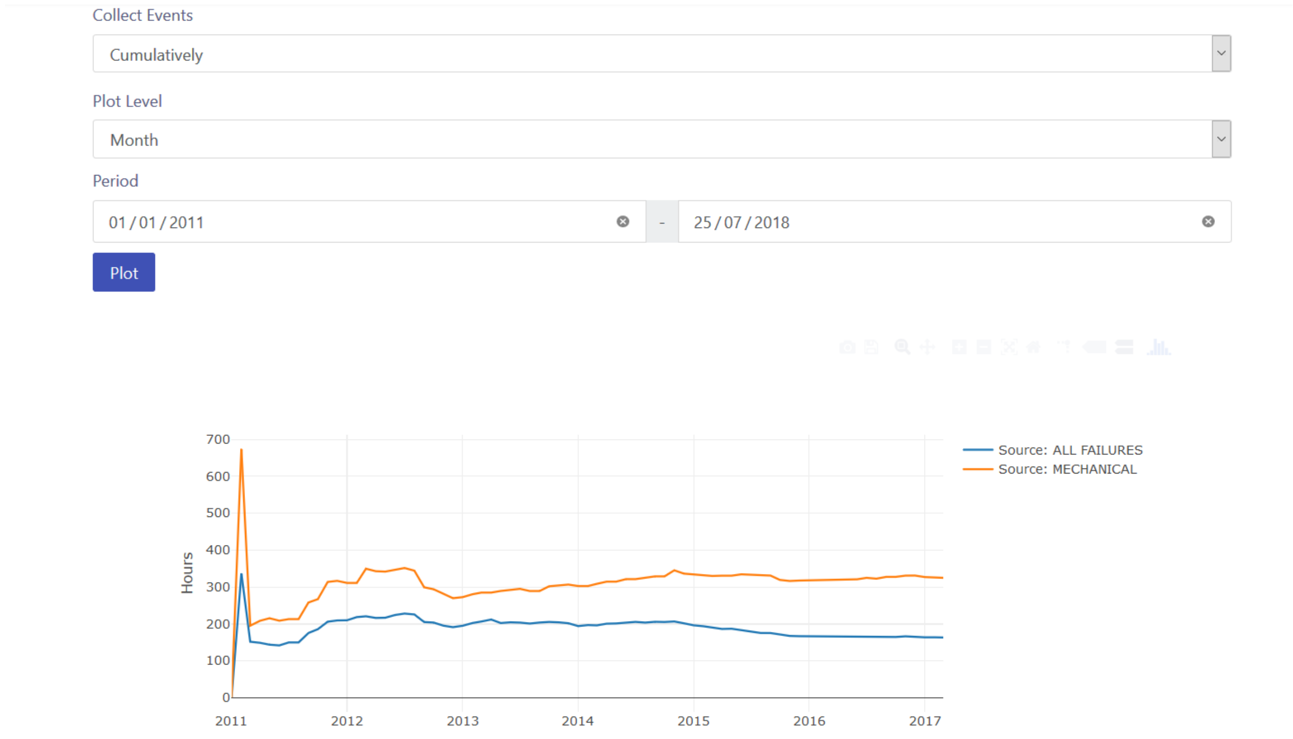

Figure 7 - MTBF of BOSSI Machine

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-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).

5.1.3 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.

5.2 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* (November 2018).

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.

<u>Implementation of COMPOSITION Solution</u>

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.

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.

5.3 Value chain risks (use cases and technology)

A risk assessment was performed for both use case (Table 4) and technology (Table 5) being used on the Value Chain Pilot. The tables bellow contains 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.

5.3.1 Use case risk assessment

Table 4 - 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	1. Critical 2. Catastrophic 3. Critical	1. Low 2. Low 3. Medium	1. Medium (6) 2. High (10) 3. High (8)	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
Equipment Monitoring and Line Visualization (UC-BSL-5)	1. Send wrong data from the equipment	1. Marginal	1. Medium	1. Medium (5)	1. Have the data collection checked regularly
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	1. Damage Polishing Machine 2. Interrupt production programme	1. Critical 2. Marginal 3. Critical	1. Low 2. Low 3. Low	1. Medium (6) 2. Medium (4) 3. Medium (6)	1. Educate participants regarding the sensor activity. The

machine (UC-KLE-1)	3. Injury to installers (technicians)				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.
Installation of vibrometer inside the polishing machine (UC-KLE-1)	1. Damage Polishing Machine 2. Wrong data received from sensor	1. Critical 2. Critical	1. High 2. Medium	1. High (9) 2. High (8)	1. Change position of vibrometer. If it doesn't work in the second position then the installation of the specific sensor inside the polishing machine is not possible. 2. Technicians should check outside the polishing machine to see if there is a failure or an indication of failure and judge based on their experience. When the machine stops then they will check the

					condition and compare it with the data received by the sensor.

5.3.2 Technology risk assessment

Table 5 - 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 Predictive Maintenance UC-BSL-2	Acoustic sensors failure due to high temperature environment they are subject to.	Marginal	Low	Medium (4)	1. Re-position sensors to a more benign environment. 2. Replace with embedded solution that has better robustness
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	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

	5. Disruption of service or productivity				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 do 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.
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 Synchronization between reality and simulation

The deployments for condition monitoring of the fans in the reflow ovens and the asset tracking system about to be 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 Predictive maintenance of fans in reflow ovens

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 8) shows what a configuration would look 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.

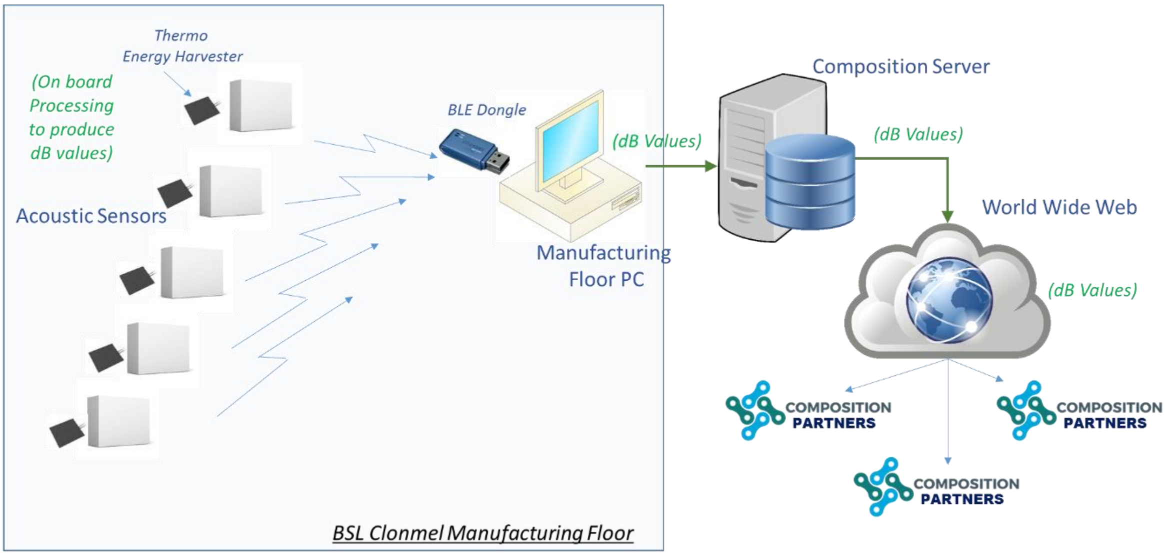

Figure 8 - Diagram of future implementation

5.4.2 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

6 Conclusion

All the presented use cases (UC-BSL-2, UC-BSL-3 and UC-KLE-1) were presented and are currently on-track 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 both UC-BSL-2 and UC-KLE-1, based on the incoming data from each partner and the failure definitions from each equipment. For KLE, a Human Machine interface was already designed and currently allows the visualization of this partner's KPI's. The same visualization interface is being adapted for BSL. Evaluation sessions on both partners were conducted and the findings from that evaluation will be used for the design of the next iteration of the HMI.

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 happy 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.

Preliminary 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