D2.2 –Set of online and offline measures for users, context and tasks

Empowering and Participatory Adaptation of Factory Automation to Fit for Workers

Abstract

Smart factories are characterized by increasing automation and increasing customization. In these dynamic environments flexible and adaptive work organization is crucial, both for productivity and work satisfaction.

The Factory2Fit project will support this development by developing adaptation solutions with which people with different skills, capabilities and preferences can be engaged, motivated and as productive members of the work community in manufacturing industries.

This deliverable describes a possible set of online measures and offline data for factory workers, working context and work tasks based on the quantified employee approach. These will allow the continuous monitoring of user operations, actions, as well as, physiological measures in order to interconnect with the processes of the factory to find the best fit between human and automation.

This deliverable presents the status of possible online measures and offline data that might be relevant for the industrial use cases and will be updated with the final set of selected measures in month 22 of this project.

Keywords:

Online measures, offline measures, monitoring, quantified self, quantified employee approach, data storage, data acquisition

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Executive Summary

This deliverable describes a possible set of online measures and offline data for workers, working context, and tasks. The set of measures are a direct outcome of the task 2.2, *online measures and monitoring*, as well as directly derived from characteristics and variables of the Adaptive Worker Model developed in task 2.1, *development of an integrated, dynamic worker model*. The list of potential online measures and offline data will be a basis for the parameters, that will be applied in the use cases of the industrial partners.

The measures defining the worker are based on the quantified employee approach. The concept of quantified self refers to the collection and analysis of personal data by wearable sensors during different kinds of activity. This approach will enable the continuous monitoring of workers' operations, actions, as well as, physiological measures in order to adapt factory processes for finding the best fit between human and automation. Furthermore, displaying the self-related data to the employee can also help him to develop a better self-understanding. When using personal data ethical aspects need to be taken into account, for instance that the privacy of the worker is not violated and the wellbeing is not at risk.

In the context of quantification of workers, tasks, and working context, a differentiation between offline data and online measures is necessary. The term online measurement in the Factory2Fit context is defined as an automatic, semi-automatic or manual measurement that is performed immediately before, during or immediately after a production process. Offline measurement will be understood as an automatic, semi-automatic or manual data acquisition, which is upstream or downstream of the actual production process.

The methodical approach used to collect potential measures was expert discussions amongst the partners in the project. The result of the expert discussion was a structure of the relevant information containing contextual data as well as data of the worker and the tasks. All collected potential online measures and offline data will be presented in section 3.

The relevant measures for the use cases of the industrial partners consists of only a few parameters at this point of the Factory2Fit project, but with the further development of the use cases, the essential information will be further made concrete.

The acquisition of the online data will be enabled primary through the Smart Sensor Network. Therefore, an interactive logging tool for the Samsung Gear S3 was developed. All types of data and formats will be handled as defined in Open Platform Communications (OPC) Unified Architecture specification, a platform-independent standard.

In relation to the overall Factory2Fit architecture, the module *Factory2Fit Repository*, contains all data concerning the factory floor and gets fed by the Smart Sensor Network. Related components are the Capability Editor and the Pre-process Plan Generator, that serve the purpose of structuring the data needed for the adaption of factory processes.

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1 Introduction

1.1 Purpose of the Document

This document (D2.2) reports the research and activities of task 2.2, *Online measures and monitoring*, and is based on task 2.1, *Development of an integrated, dynamic worker model*. The purpose of this deliverable is to present a potential set of online and offline measures for quantification of the dynamic worker model. The collected information is based on the characteristics and parameters of the worker, the tasks, the factory equiment and the working context as described in Deliverable 2.1 (public).

The description of possible online measures of workers, context and tasks are based on the quantified employee approach. This will allow continuous monitoring of user operations, actions as well as the measurement of physiological data in order to interconnect them with the processes of the factory to find the best fit between human and automation. The quantified worker approach will be explained and transferred to the Factory2Fit framework. Then, definitions for online measurements and offline data suitable for the Factory2Fit project will be presented.

Section 2.4 of this deliverable explains the process how the relevant online and offline information was defined as well as the structure of the set of measures and the features of the measurement. After that, all identified measures that are feasible and useful are presented in section 3. The equipment data are collected in the current phase of the project and will be complemented in a later stage of Factory2Fit. This will be presented in the update of this deliverable. Derived from all possible sources of information, the industrial partners describe the usage of selected measures in their use cases.

Section 4 of this deliverable elucidates the process of the data collection and how the data will be processed within the Factory2Fit architecture as described in Deliverable 1.4, *Adaption architecture*.

1.2 Intended readership

D2.2 is a public document (Dissemination Level PU) and therefore addresses the European Commission, the Factory2Fit Project Officer, the members of the Factory2Fit consortium, members of other H2020-funded projects as well as a broad range of different target audiences from factory workers, employers, industrial networks and associations, to other national and EU-funded projects, Commission staff, media, and the wider public. Even though the online measures and offline data have been defined based on the needs of the Factory2Fit project, the results can be utilised and adapted by other projects and organizations that intend to utilise similar technologies.

1.3 Relationship with other Factory2Fit deliverables

This deliverable is a direct outcome of the Task 2.1, *Development of an integrated, dynamic worker model*, and is directly linked to Deliverable 2.1, *Dynamic worker model*. In Task 2.2, *Online measures* *and monitoring*, the measurements were derived from the described characteristics and the respective parameters of the Worker Model. These measurements will be presented in part in the Worker feedback dashboard developed in task 2.3, due in month 9 of the Factory2Fit project.

While D1.1, *Enabling Technologies*, gives an overview of potential devices to measure the worker status, this deliverable describes the online measures and offline data that have been chosen to support the Factory2Fit user model. Based on the industrial requirements described in D1.2, *Industrial Requirements*, and the progressing clarification of the use cases (T1.4), the individual preliminary measures for each pilot will be presented. In Task 2.4 these measurements will be validated by pre-tests and in industrial environments, starting at month 9 and resulting in Deliverable 2.4, *Validated setup of measures*.

1.4 Acronyms and abbreviations

Abbreviation	Description
API	Application Programming Interface
Dx.x	Deliverable x.x (e.g. D2.1 = Deliverable 2.1)
EAWS	Ergonomic Assessment Worksheet
EFFRA	European Factories of the Future Research Association
EU	European Union
HMI	Human-machine interface
JSON	JavaScript Object Notation
MES	Manufacturing Execution Systems
MQTT	Message Queue Telemetry Transport
OPC UA	Open Platform Communications Unified Architecture
p	per
PU	Public
S3	Samsung Gear S3
SCADA	Supervisory Control and Data Acquisition
SQL	Structured Query Language
SSN	Smart sensor network
TAU	Tizen Advanced UI

UWP	Universal Windows Platform
VDI	Verein Deutscher Ingenieure (English: Association of German Engineers)
XML	Extensible Markup Language

Table 1: List of Abbreviations

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2 Approach to define relevant measurements in Factory2Fit

2.1 Description of Factory2Fit-setting

Smart factories represent the factories of the future and a key factor of Industry 4.0 [16]. Industry 4.0 and the increasing digitalization of work allow a more individual production to satisfy customer requirements, enable last-minute changes and more flexible responses to failure. So, smart factories are not only characterized by higher automation, they also go along with higher customization. At the same time, many new opportunities for the worker appear while the factory environment and workplace design are changing. Smart assistance systems carry high potential to reduce stressors related to work, enable workers to fulfil their tasks in a better way and focus on value-added activities. Within smart factories, information of the worker could be used to adapt processes.

The Factory2Fit project will support the change towards adaptive smart factories by developing adaptation solutions with which people with different skills, capabilities and preferences can be engaged and motivated as productive members of the work community in manufacturing industries. To reach this aim, Factory2Fit follows a worker-centered approach in which a worker model builds the center of factory process adaptation [17]. A Worker Model defines a worker and his/her abilities by describing various worker characteristics [18] and can include worker's preferences, knowledge and attributes generally, or for a particular task. Factory2Fit Worker Modelling methodology consists of three main parts: Worker Model, Adaptive Worker Model, and Worker Profile. The first part, Worker Model, is defined as a static model including general worker characteristics. The Adaptive Worker Model represents a dynamic Worker Model describing the relations between worker characteristics and multiple other elements in the working area. Last but not least, the Worker Profile refers to a machine-readable instance of a worker model representing a specific worker. In Deliverable D2.1 this was described in more detail. In the current deliverable, the aim is to describe a potential set of online measures and offline data of users, context and tasks that will be used for worker modelling. In Factory2Fit, continuous monitoring of user operations, actions and physiological measures should reveal data that can be interconnected with the factory processes and be used to find the best fit between human and automation.

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2.2 The quantified worker approach

In the recent years, wearable devices spread across the world and continue to enter every part and every second of the human life. The variety of devices is huge and they are increasingly entering everyday life. The application in health industry and fitness tracking is wide spread [1, 11]. People use these devices for getting feedback on their sport activities, sleep, stairs climbings, calories burned, heart rate, cognitive activity like quantifying the process of reading, and other person-based information [9, 12]. The main aim is to quantify and visualize such activities to foster advantageous behaviour [19]. The possibilities are almost endless. Wearable devices can raise awareness of personal health and even predict imminent health problems [1].

Additionally, such devices create so called *big data* that have an immense potential for facilitating, for instance, the discovery of risk factors for diseases. A variety of different sensors that are installed in wearable devices collect a huge amount of data with high frequency and large variety [10]. The data can be used to detect correlations between risk factors and diseases, as well as, facilitate actions to eliminate modifiable risk factors. A precondition for that is the definition of specific risk factors for specific diseases. Through wearable devices, this can be achieved.

A recent publication refers to a study with one participant over the course of 24 months and 43 participants over the course of 6 months [1]. The participants wore up to 7 different devices at a time to collect a large variety of physical data. It is shown how wearable devices can raise awareness of personal health and even predict imminent health problems only with the integrated sensors of the wearable devices. Thereby, the time of absence caused by illness might be reduced due to an earlier intervention or earlier return form health related absence [28]. Fostering healthy behavior can be a key factor for preventing pathogenesis [27].

Wearables like smartwatches include the possibility of localization of the worker within the factory. This could be used for lowering the risk of collisions as well as the observance of predefined security zones, hence increasing safety at work. Additionally, requested help can be send immediately and directly to the workers' location [29]. Especially, when handling heavy products, an online optimization of the route through the factory is possible.

The trend of self-quantification has become a movement, called *Quantified Self* [13, 14]. This movement employs technology to promote self-awareness through quantification of one self. Personal data is being collected by wearable sensors and processed during different kinds of activity, like sports, work or sleep. The declared objective is to gain key insights on the own development. Hence, setting goals and quantifying the progress should encourage people to develop personally and getting self-aware and mindful [15].

Besides quantifying the user, many technical solutions include gamification elements that are supposed to further support self-development. For that purpose, the principles of game design and game mechanics are applied in non-game contexts to solve problems, complete tasks or engage the user [3].

Self-monitoring, analyzing the continuous collected data and the provided feedback together are aiming for fostering quantification of self and to better care for one's self [2]. This is accomplished

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through quick and direct feedback of the behavior shown by the user. This immediacy reinforces a distinct behavior and increases the effectiveness of the reinforcement [4].

The application of self-quantification on the factory environment is still to be examined scientifically, but there might exist many possibilities to foster personal development of the worker, health at work, an optimized learning process, and work satisfaction:

- The approach of *Big Data* collection with (wearable) sensors, for example smartwatches, can be used to analyse the production process as a whole and identify possible bottlenecks in production and impairing stressors for workers.
- The idea of a quantified self at work can make the personal progress visible, (e.g., growth of knowledge, promotion at work or job enlargement) and through gamification enhance motivation even further. The worker can be enabled to directly evolve himself in the desired direction.
- Tracking physiological conditions of the worker may help him to detect health issues earlier or directly see the progress of a healthier lifestyle and health behavior at work. This might also motivate to reinforce health behavior, and thereby reduce absence at work due to illness or alter specific job characteristics.
- Learning new tasks or refreshing infrequently used procedures might be supported by assessing the existing knowledge and quantifying the progress of knowledge in order to better assign proper learning content and again motivate the worker to gain more knowledge.

Overall, the quantified worker approach in Factory2Fit aims on increased worker satisfaction through reducing stressors and supporting personal development, health behavior as well as knowledge of the whole relevant work content.

When applying this approach, it is needed to take the wellbeing of the worker, data privacy, and equity among all workers into consideration. Besides the motivational function of quantifying the personal progress, potential negative consequences need to be considered. Workers might become disappointed or over-motivated so that the worker develops an excessive and unhealthy commitment to the job. Concerning the processing of the data, it is utterly important that only the worker will decide which data will be collected and how the data is used. There should be no disadvantages if the worker decides to not disclose any data. Furthermore, the possibility to compare the workers among themselves in order to separate out less productive workers should be ruled out.

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2.3 Definition of online measures and offline data

According to the standard VDI 5600 Production management systems (Manufacturing Execution Systems – MES) [8], the goal of data collection in the production domain is the event-driven recording of all relevant data from the shop floor. This concerns:

- Operating data (e.g. operating data acquisition in the sense of the order of the data)
- Machine data
- Process data
- Quality Data
- Personnel data (e.g. personnel working time recording)
- and other

In addition to automatic data transfer, semi-automatic (e.g., scanners) and manual data acquisition are possible. The collected data is used to provide all other MES tasks with the relevant information (e.g., process monitoring, plant monitoring, tracking / tracing). In addition, current changes in the production process are signaled promptly. In certain situations, direct effects on the production process, e.g. by locking the machine start, are possible.

The data is collected centrally via terminal workstations at central MES systems; decentralized e.g. via SCADA workstations at decentralized control rooms, via specialized data acquisition terminals, through direct machine data acquisition or in the future also by smart devices (e.g. smartphones, smart watches, smart wristbands).

The identification of the "data collection object", for example, a process step for which a result message is to be recorded, is frequently carried out with barcode support. In addition to these modern methods, there is also a paper-based approach, which transfers characters or even primitive symbols (for example counting lines) to the paper with the aid of writing tools.

The type of measurement can be divided into online measurement and offline measurement based on the temporal context and the connection to the production process. The term *online measurement* in the Factory2Fit context is defined as an automatic, semi-automatic or manual measurement that is performed immediately before, during or immediately after a production process and has the following attributes [5, 6, 7]:

- Temporally linked to the process; during the task

- Direct (detecting changes without significant difference between measurement result and actual value, directly controlled by other entities or directly influences the system without human interaction)

- High frequency of measurement in relation to the frequency of the process

- Predominantly virtual, connected to the digital infrastructure

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Online data gives a feedback on the physical condition of the worker and the performance of the system. *Offline measurement* will be understood as an automatic, semi-automatic or manual data acquisition, which is upstream or downstream of the actual production process and has the following attributes [5, 6, 7]:

- Temporally detached from the process; pieces taken out of the process; retrospective and needs reconstruction of the situation
- Indirect (results of measurement might be available after significant changes are possible, not directly controlled by other entities or does not directly influence the system, human interaction is needed)
- Low frequency of measurement in relation to the frequency of the process; irregular measuring
- Predominantly real/physical, not connected to the digital infrastructure

The so-called master data management is distinguished from the operational data collection, by means of which data defining and specifying the production processes are recorded, e.g. work plans, parts lists (bill of materials), work instructions, drawings, parameters / recipes, equipment and device control programs, error catalogs, documents, etc.

Compared to the data acquired during the operational data collection, the data of the master data management are more of a static nature and are therefore seldom changed.

2.4 Methodical approach

2.4.1 Methodology

The online measurement and offline data are derived from the worker model described in Deliverable 2.1, *Dynamic worker model*. The worker model represents various worker characteristics of the worker, including wellbeing, generic properties, skills, preferences as well as the current work context. In addition, task characteristics are considered as well.

The main aim was to provide a work-related abstraction of employees and to define, what variables and characteristics can and / or should be assessed to develop a comprehensive Adaptive Worker Model. Therefore, through an expert discussion, ideas of relevant variables were collected and the structure of the model was designed. After the review of the project partners, they prioritized the collected variables and characteristics. In the end, the worker model was developed as presented in D2.1.

The characteristics of the worker model (e.g. emotional states) are described with several variables (e.g. boredom, frustration). These variables are determined by several parameters (or measures). To clarify, which variables are relevant and how the parameters can be measured, each project partner

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collected information about the relevant measures for the variables and provided information about the measurement process.

2.4.2 Structure of collected measures

Factory2Fit D2.1 introduced the characteristics included in Worker Model and Adaptive Worker Model, with the parameters of every variable needed to define each worker characteristic. These parameters should be measured with the proper devices in order to develop a complete Worker Model. Based on the results presented in D2.1, where the relevant categories for describing and shaping the Worker Model are provided (see Figure 1), further detailing is necessary to match the Worker Model's requirements with the sensors and information sources being available at the pilots of Factory2Fit and to identify additional sensors or sources being required to collect the necessary information. Furthermore, this detailing provides the necessary information which data, data sources and interfaces need to be handled by or included in the Factory2Fit Repository and/or other modules described in D1.4, *Adaption architecture*.

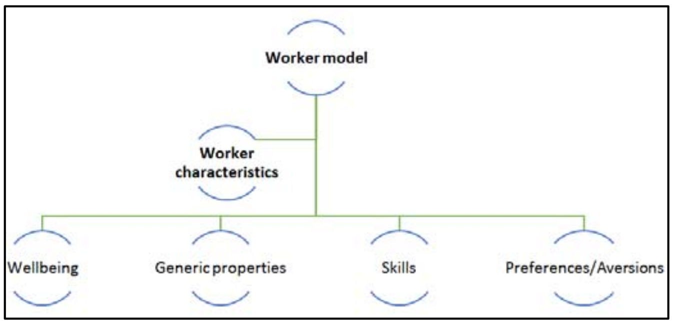

***Figure 1:** Worker Model characteristic's categories.* (taken from Factory2Fit D2.1)

Whereas D2.1 describes the Worker Model with its categories, characteristics, variables and parameters from the methodical point of view, D2.2 describes these aspects from the technical point of view to provide the necessary information for implementing the Worker Model and gathering the information during piloting. While D2.1 describes the hierarchy of the categories, characteristics and variables (see Figure 2), D2.2 focuses on the parameters (Measurements/Data), only.

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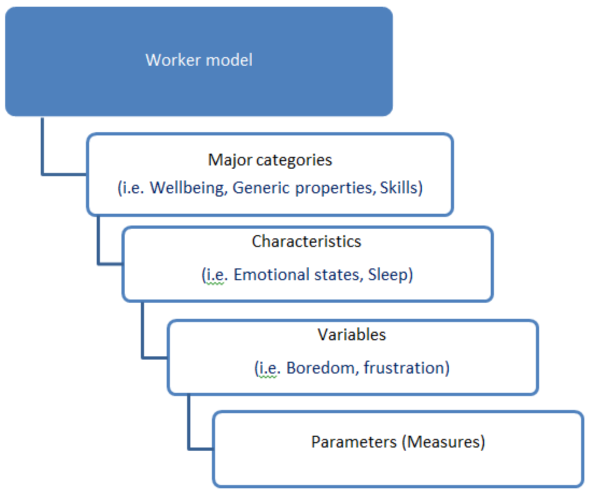
Worker model
Major categories
(i.e. Wellbeing, Generic properties, Skills)
Characteristics
(i.e. Emotional states, Sleep)
Variables
(i.e. Boredom, frustration)
Parameters (Measures)

Figure 2: *Worker characteristic analyses.* (taken from Factory2Fit D2.1)

To allocate the different parameters being described in this document according to their potential usage within the Worker Model of Factory2Fit, they are grouped following the Adaptive Worker Model structure of D2.1 (see Figure 3). This illustrates the dimensions of the four aspects being considered in the model and also helps understanding the aim of each category of characteristics.

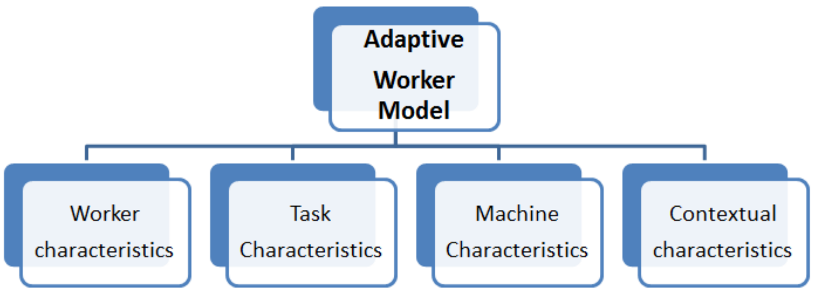

Figure 3*: Adaptive Worker Model*(taken from Factory2Fit D2.1)

Besides classifying the Adaptive Worker Model Parameters according to their aspect of use, additional detailing regarding the utilized manner of data acquisition is need. Therefore, the four categories of the Adaptive Worker Model to describe the parameters are split in the two following subcategories:

a) **Online measurements:** parameters included in online monitoring sections are based on the measurements acquired from certain devices provided by the Smart Sensor Network (SSN) and the factory environment. This kind of monitoring concerns the measurements that are

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derived directly from a certain worker-specific self-monitoring device, e.g. blood pressure, or are provided directly by a certain piece of equipment, e.g. machine state.

b) **Offline data:** measurements included in this category are derived from questionnaires and interviews, e.g. specific physical disabilities and knowledge on relevant tasks, as well as from other non-real-time information systems within the pilot environments, e.g. machine specifications.

2.4.3 Properties of the measures

Besides the contextual usage of the measures and data potentially included in the Adaptive Worker Model and the type of data acquisition, additional information is needed to define, for example, the interfaces and database tables to design the Factory2Fit Repository and the Worker Model. Therefore, the measurements and data listed in Chapter 3 provide additional information regarding the following aspects:

- **Dimension:** the dimension information provides the classification for the worker online measures or offline data regarding the multiple worker's abilities and the type of information. The abilities of the worker can be described with the dimensions: physical, cognitive, sensorial and external. This describes the relation of the data compared to the entity *worker*.

- **Data source:** besides the type of information, the intended source of information needs to be defined. Possible categories for the data source are: (wearable and environment) sensors, automatic video analysis, questionnaires, machine data, self-report, personal file, interview, observation, other documents.

- **Unit:** some of the information and measures processed within the Factory2Fit architecture have a specific unit. To avoid misinterpretation and a lack of clarity the units being used within Factory2Fit are defined.

- **Data Type:** for data storage and data processing, the data types being utilized for each parameter need to be defined. For a detailed explanation of existing data types please see Table 8: Standard data types.

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- **Measuring rate**: to describe the required or possible time intervals for updating parameter values, the measuring rates are defined for each parameter. Especially for Online Measurements, this information determines suitable sensors and protocols.

- **Level of Measurement:** the level of measurement describes the scale of the data being collected from workers e.g. in questionnaires, and provides information regarding possible computational operations. Possible categories for data source are: interval, ratio, ordinal, and nominal.

The described details are provided for each parameter, as far as it is feasible or possible at the current stage of the project. With further detailing and definition of the pilot's use cases, including e.g. selecting the involved equipment at the factories, the definitions and descriptions can be refined and finalized.

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3 Online and offline measures

The collected potential measures for the Factory2Fit Adaptive Worker Model are being presented in this section. First, the measures for the worker are shown, followed by measures for context and for tasks.

For this section as well as for the presented measures, it has to be considered, that the information sources presented in this document have been collected during the conceptual phase of the use cases. The final list of actually used measures will be documented in the update of this deliverable in month 22. Furthermore, not all of the measures will be used due to ethical concerns. Nevertheless, these measures are mentioned for the sake of completeness.

3.1 Measures of the workers

Relevant measures concerning the worker are presented in this section. First, possible measures collected by the means of online measurements are listed. After that, offline data acquisition is presented. The measures are divided into different sections (e.g., well-being or physical activity), based on the worker characteristics of the adaptive worker model. It has to be considered, that some measurements can be used to determine several variables (e.g., heart rate can be used as an indicator for physical activity and emotional arousal).

3.1.1 Online measurement of workers

Measures	Dimension	Data source	Unit	Type of Data	Measuring rate	Level of measurement
Online measures for well-being and emotional states						
Respiratory patterns	physical	Sensors	Rpm	Integer	<1s	ratio
Facial expression	physical	Video analysis			<1h	categorial
EEG-signals	physical	Sensors	V	Integer	<1s	ratio
Galvanic skin conductance	physical	Sensors	S	Integer	<1s	ratio
Blood lactate level	physical	Sensors	mM	Integer	<1h	ratio
Heart rate	physical	Sensors	Bpm	Integer	<1s	ratio
Heart rate variability	physical	Sensors	Ms	Integer	<1s	ratio

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Measures	Dimension	Data source	Unit	Type of Data	Measuring rate	Level of measurement
Online measures for well-being and emotional states						
Subjective feeling	internal cognitive	Questionnaire		Integer	<1d	ordinal
Online measures for physical activity						
Length of sedentary periods	physical	Acceleration sensors	Min	DateTime	<1min	interval
Length of standing periods	physical	Acceleration sensors	Min	DateTime	<1min	interval
Step count	physical	Sensors of e.g. smartwatch	1	Integer	1min	Interval
Online measures for social interaction						
Number of instances of social interaction	external	Sensors	1	Integer	<1min	interval
Online measures for sleep						
Length of restful sleep for a day	sensorial	Sleep metrics from wearable sensors	Min	DateTime	1d	interval
Online measures for work satisfaction						
Perceived workload	cognitive	Questionnaire	%	Integer	<1h	ratio
Online measures for work performance						
Duration per task	external	Sensors	Min	Integer	per task	interval
Number of tasks to be performed	external	Sensors	1	Integer	1d	ratio
Quality of task performance	external	Sensors		String	per Task	ordinal

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Measures	Dimension	Data source	Unit	Type of Data	Measuring rate	Level of measurement
Online measures for work performance						
Proportion of machine being in running state	external	Machine data	%	Integer	p. machine state change	interval
Duration of the longest running period of the production	external	Machine data	Min	DateTime	1d	interval
Number of completed tasks	external	Machine data	1	Integer	1d	interval
Recovery time from machine failure	external	Machine data	Min	DateTime	per failure	interval
Online data for work rhythm						
Length of continuous work periods per workday	external	Sensors	Min	Integer	1min	interval
Timing of work periods	external	Shift schedule, sensors			1min	

Table 2: Online measures of workers

3.1.2 Offline data of workers

Data	Dimension	Data source	Unit	Type of Data	Measuring rate	Level of measurement
Offline data for work rhythm						
Number of breaks	external	Self-report	1	Integer	<1d	ordinal

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Data	Dimension	Data source	Unit	Type of Data	Measuring rate	Level of measurement
Offline data for work satisfaction						
Work satisfaction subjective feeling	cognitive	Questionnaire		Integer	once	ordinal
Motivation	cognitive	Questionnaire		Integer	<1y	ordinal
Perceived competence	cognitive	Questionnaire		Integer	1d	ordinal
Work-day specific subjective feeling	cognitive	Questionnaire		Integer	1d	ordinal
Offline measures for generic properties						
Year of birth	physical	Personal file	Y	Integer	once	ratio
Height	physical	Personal file	M	Integer	once	ratio
Gender	physical	Personal file	Y	String	once	nominal
Learning traits	cognitive	Questionnaire		Array	once	nominal
Specific disabilities	physical	Questionnaire		String	once	nominal
Offline data for work experience						
Job Tenure	cognitive	Personal file	Y	Integer	once	interval
Comprehension of processes	cognitive	Questionnaire, Interview, Observation	%	Integer	<1y	ratio
Knowledge of specific task	cognitive	Questionnaire, Interview, Observation	%	Integer	<1m	ratio
Offline data for language skills						
Intercultural competences	cognitive	Questionnaire		String	once	ordinal
Language skills	cognitive	Personal file		String	once	ordinal

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Data	Dimension	Data source	Unit	Type of Data	Measuring rate	Level of measurement
Offline data for social skills						
Ability to cooperate	cognitive	Observation, Questionnaire		String	<1y	ordinal
Ability to deal with conflict	cognitive	Observation, Questionnaire		String	<1y	ordinal
Communication abilities	cognitive	Observation, Questionnaire		String	<1y	ordinal
Offline data for preferences and aversions						
Preference for tasks	cognitive	Questionnaire		Array	once	nominal
Preference for shift model	cognitive	Questionnaire		Integer	once	nominal
Preference for tools	cognitive	Questionnaire		Array	once	nominal
Preference for level of participation	cognitive	Questionnaire		Integer	once	nominal
Preference for personal feedback	cognitive	Questionnaire		Integer	once	nominal
Preference for personal adaption	cognitive	Questionnaire		Integer	once	nominal
Preference for working hours /shift	cognitive	Questionnaire		Array	once	nominal
Preference for coworkers	cognitive	Questionnaire		Integer	once	nominal

Table 3: Offline measures of workers

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3.2 Measures for the context

Relevant measures concerning the working context, including environment, social and organizational context are presented in this section. First, possible measures collected by the means of online measurements are listed. After that, offline data acquisition is presented.

3.2.1 Online measurement of context

Measures	Data source	Unit	Type of Data	Measuring rate
Online measures for environment				
Room temperature	Sensors	°C	Integer	<1min
Outside temperature	Sensors	°C	Integer	<1min
Relative humidity	Sensors	%	Integer	<1h
Air velocity	Sensors	m/s	Integer	<1min
Sound pressure level	Sensors	dB(A)	Integer	<1min
Vibration intensity: acceleration	Machine sensors	M	Integer	<1min
Vibration intensity: exposure duration	Machine sensors	S	Integer	<1s
Illumination level	Sensors	Lux	Integer	<1min

Table 4: Online measures for context

3.2.2 Offline data of context

Data	Data source	Unit	Type of Data	Measuring rate
Offline data for social context				
Coordination requirements	Planning documents		String	once
Communication requirements	Planning documents		String	once
Dependability on others	Planning documents		String	once

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Data	Data source	Unit	Type of Data	Measuring rate
Offline data for organizational context				
Shift schedule	Planning documents		DateTime	<1w
Current work hours	Sensors or user input	Min	DateTime	<1d
Work break schedule	Planning documents		DateTime	<1w

Table 5: Offline data for context

3.3 Measures for the tasks

Relevant measures concerning the work tasks are presented in this section. First, possible measures collected by the means of online measurements are listed. After that, offline data acquisition is presented.

3.3.1 Online measurement of tasks

Measures	Data source	Unit	Type of Data
Online measures for general task characteristics			
Tact rate		Sec	time
Tolerance for accuracy			Integer or Float or String
Time share of sub-tasks		%	Float
Duration of (sub)tasks		Sec	time
Interruptions			List
Number of (sub)tasks		1	Integer
Mandatory qualification level	Catalogue		Integer or Float; String or List

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Measures	Data source	Unit	Type of Data
Online measures for decisions			
Availability of necessary information for decisions	Personal rating		Integer or Float or String
Level of cognitive regulation			Integer or Float, list; array
Online measures for ergonomics			
Duration of recreation intervals		Sec	time
Number of recreational intervals		1	Integer
Online measures for materials / product			
Number of materials handled		1	Integer

Table 6: Online measures for tasks

3.3.2 Offline data of tasks

Data	Data source	Unit	Type of Data
Offline data for general task characteristics			
Weights to be handled		Kg	Integer
Forces to be applied		N	Integer
Buffer times		S	DateTime
Type of the task	Catalogue		String
Number of tasks require different competencies		1	Integer
Offline data for process results			
Number of task intervention possibilities		1	Integer or List
Predictability			Integer or Float or String

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Data	Data source	Unit	Type of Data
Offline data for decisions			
Autonomy for decision, number of task execution alternatives		1	Integer or List
Criticality of decision, implication of decisions			Integer or Float or String
Number of decisions		1	Integer or List
Offline data for task performance dynamics			
Likelihood of process or task changes, number of changes per period		1	Integer or Float or String
Predictability of changes			Integer or Float or String
Controllability of changes, number of possible interventions		1	Integer or Float or String
Likelihood of disturbances, number of disturbances per period		1	Integer or Float or String
Predictability of disturbances			Integer or Float or String
Controllability of disturbances, number of possible interventions			Integer or Float or String
Limitations of response time		%	Time
Offline data for ergonomics			
EAWS evaluation points	Observation and measurements	Pts	Float or List
Required body postures		1	Integer or List
Travel distances		M	Integer or Float or String

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Data	Data source	Unit	Type of Data
Offline data for materials / product			
Material supply	Observation		Integer or Float or String
Offline data for collaboration			
Coordination requirements		1	Integer or String or List
Communication requirements		1	Integer or String or List
Dependability on others, number of relations		1	Array

Table 7: Offline measures for tasks

3.4 Users, Context and Tasks in relation to the industrial use cases

In this section, the connection to the use cases of the industrial partners is drawn. A short description of the use cases which are still in conceptual phase is given. The relevant measures are derived from the use cases and are named.

3.4.1 Requirements for the relevant variables for Prima Power

Worker related variables:

- User name
- Password
- Name
- Roles / privileges
- Work shifts
- Physical state: Heart rate, steps

These variables are related to the use case where the Human-Machine Interface (HMI) could be adapted based on the user. Authentication of the user is needed to be able to modify the HMI corresponding to the worker preferences. In this use case it could be possible to set different roles/rights for certain functionalities to control the machine (e.g. modify material database, modify laser technology parameters, modify tooling parameters, etc.).

Another use case with worker related variables is the worker dashboard (see D2.3, *Worker feedback dashboard*). Dashboard could give information of the machine production in relation to the worker personal data (e.g. heart rate, steps, etc.) From this view, it could be possible to monitor the "efficiency" of the production per day and per shift. Data is collected from the machine and from the worker wearable smart sensors and they are aggregated in the dashboard view.

Order/Task related variables:

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- Name
- Order number
- Due date
- Duration
- Phases (Blanking, cutting, bending, painting, welding, assembling, etc.)

These variables are related to the use case where production orders/tasks could be scheduled automatically based on certain rules. This use case could use the "Task distribution engine" algorithms to define the most optimal scheduling policy /route for the order in the manufacturing flow. In a more complex order handling there could be different phases for the parts to go through the production flow. After the part is cut it could go to the bending, welding, painting, etc. phase – depending on the design. If there is more than one logical place to complete certain phases it could be difficult to assign what is the most optimal way to produce the part flow and any automation or suggestion to this flow could improve the efficiency of the system.

3.4.2 Requirements for the relevant variables for Continental

Within Continental use case the following variables are related to the worker:

- Name
- User name
- Password
- Skill/educational level
- Preferred work shifts
- Preferences for work content/area
- Rate of tasks, performed without failure
- Physical state: Heart rate, steps
- Well-being: Satisfaction, motivation

When the worker operates the measurement machine, he first needs to log on through user name and password. The worker could see the personalized dashboard every time when logged on a PC at a measurement machine. Depending on the educational level, the system could provide suggestions for skill development (e.g. proposal of video lessons). In addition, the task distribution could be done corresponding to the workers performance and his preferences, as far as they are not in conflict with other variables in the context, that omit to respect the preference. For example: worker does not like to run a certain machine, but there is currently no one else available, who has the needed skills - so he has to do the task, even if it is against his preference. The complementation of the dashboard information with physical information is another suggestion within the use case.The following task related variables were identified:

To support the worker with most relevant information the dashboard should content the upcoming tasks (maybe two or three), their current priority, and the scheduling. Beside the dashboard, there should exist an overview of all currently addressed, running and next forecasted tasks. Those tasks and their prioritization could be provided filtered to certain variables: the specific laboratory, where

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the task shold be conducted, worker, measurement machine type, measurement machine, or with the possibility to filter for any variable of choice. Recording the technical performance, e.g. task duration or interruptions (not caused by the worker, but by technical issues) could help to identify areas of improvement, the problem solving and finally to motivate the staff by visualization of the improvement.

Order/Task related variables:

- Name
- Task number
- priority
- Due date/time
- Planned/real duration
- Sub tasks (number of parts, measurement tasks)
- Interruptions
- Machine / machine type
- Location of machine
- Origin of the task

3.4.3 Requirements for the relevant variables for UTRC-I

Pilot workshop of United Technologies Corporation (UTC) use case HVAC-Culoz performs manual operations in assembly of Air Handling Units (AHU). There are main similarities between different AHU orders in terms of size and the component that can help to classify them. However, since each AHU is configured regarding to specific customer requirements, assembly complexity varies for each order and therefore, specific AHU orders requires specific competence levels. Monitoring the progress of workers with novice and intermediate skill levels as long as with their stress level regarding to complexity of the new AHU orders are very important for continuous development of worker competency, satisfaction and predictability of manufacturing performance. Hence, HVAC-Culoz envisages having the following variables :

Worker related variables:

- User name
- Password
- Name
- Competence level
- Work shift

Order/Task related variables :

- Order number
- Due date
- Expected Duration
- Options of order

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- Type of the order
- Size of the order
- Assembly tasks (from process/precedence plan)

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4 Acquisition and processing of data

In this section, the technical basis for the acquisition and the concept of the architecture for processing the data will be described. The technical basis for the measurement of the relevant parameters is the smart sensor network. In addition to the developed Factory2Fit Worker feedback dashboard (see Deliverable 2.3, *Worker feedback dashboard*), a possible solution for data acquisition with the Samsung Gear S3 will be presented.

4.1 Type of data and format

Types of data and formats will be handled as defined in OPC Unified Architecture (OPC-UA) specification.

4.1.1 General

OPC UA is a platform-independent standard through which various kinds of systems and devices can communicate by sending Messages between Clients and Servers over various types of networks. It supports robust, secure communication that assures the identity of Clients and Servers and resists attacks. OPC UA defines sets of Services that Servers may provide, and individual Servers specify to Clients what Service sets they support. Information is conveyed using OPC UA-defined and vendor-defined data types, and Servers define object models that Clients can dynamically discover. Servers can provide access to both current and historical data, as well as Alarms and Events to notify Clients of important changes. OPC UA can be mapped onto a variety of communication protocols and data can be encoded in various ways to trade off portability and efficiency.

4.1.2 Design goals

OPC UA provides a consistent, integrated AddressSpace and service model. This allows a single OPC UA Server to integrate data, Alarms and Events, and history into its AddressSpace, and to provide access to them using an integrated set of Services. These Services also include an integrated security model. OPC UA also allows Servers to provide Clients with type definitions for the Objects accessed from the AddressSpace. This allows information models to be used to describe the contents of the AddressSpace. OPC UA allows data to be exposed in many different formats, including binary structures and XML documents. The format of the data may be defined by OPC, other standard organizations or vendors. Through the AddressSpace, Clients can query the Server for the metadata that describes the format for the data. In many cases, Clients with no pre-programmed knowledge of the data formats will be able to determine the formats at runtime and properly utilize the data.

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4.1.3 AddressSpace Model

The set of Objects and related information that the OPC UA Server makes available to Clients is referred to as its AddressSpace. The OPC UA AddressSpace represents its contents as a set of Nodes connected by References. Primitive characteristics of Nodes are described by OPC-defined Attributes. Attributes are the only elements of a Server that have data values. Data types that define attribute values may be simple or complex.

4.1.4 Data Type Model

The DataType Model is used to define simple and structured data types. Data types are used to describe the structure of the Value Attribute of Variables and their VariableTypes. Therefore each Variable and VariableType is pointing with its DataType Attribute to a Node of the DataType NodeClass. In many cases, the NodeId of the DataType Node – the DataTypeId – will be well-known to Clients and Servers. In addition, other organizations may define DataTypes that are well-known in the industry. Well known DataTypeIds provide for commonality across OPC UA Servers and allow Clients to interpret values without having to read the type description from the Server. Therefore, Servers may use well-known DataTypeIds without representing the corresponding DataType Nodes in their AddressSpaces.

In other cases, DataTypes and their corresponding DataTypeIds may be vendor-defined. Servers should attempt to expose the DataType Nodes and the information about the structure of those DataTypes for clients to read, although this information might not always be available to the Server.

The DataType points to an Object of type DataTypeEncodingType. Each DataType can have several DataTypeEncoding, for example “Default”, “UA Binary” and “XML” encoding. Services allow clients to request an encoding or choosing the “Default” encoding. Each DataTypeEncoding is used by exactly one DataType, that is, it is not permitted for two DataTypes to point to the same DataTypeEncoding. The DataTypeEncoding Object points to exactly one Variable of type DataTypeDescriptionType. The DataTypeDescription Variable belongs to a DataTypeDictionary Variable.

Since the NodeId of the DataTypeEncoding will be used in some mappings to identify the DataType and its encoding, those NodeIds may also be well-known for well known DataTypeIds. The DataTypeDictionary describes a set of DataTypes in sufficient detail to allow Clients to parse/interpret variable values that they receive and to construct values that they send. The DataTypeDictionary is represented as a variable of type DataTypeDictionaryType in the AddressSpace, the description about the DataTypes is contained in its value attribute. All containing DataTypes exposed in the AddressSpace are represented as Variables of type DataTypeDescriptionType. The value of one of these variables identifies the description of a DataType in the Value Attribute of the DataTypeDictionary.

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The DataType of a DataTypeDictionary Variable is always a ByteString. The format and conventions for defining DataTypes in this ByteString are defined by DataTypeSystems. DataTypeSystems are identified by NodeIds. They are represented in the AddressSpace as Objects of the ObjectType DataTypeSystemType. Each Variable representing a DataTypeDictionary references a DataTypeSystem Object to identify their DataTypeSystem.

A client shall recognise the DataTypeSystem to parse any of the type description information. OPC UA Clients that do not recognise a DataTypeSystem will not be able to interpret its type descriptions, and consequently, the values described by them. In these cases, Clients interpret these values as opaque ByteStrings.

Different kinds of DataTypes are handled differently regarding their encoding and according to whether this encoding is represented in the AddressSpace. Built-in DataTypes are a fixed set of DataTypes. They have no encodings visible in the AddressSpace since the encoding should be known to all OPC UA products. Examples of Built-in DataTypes are Int32 and Double.

Simple DataTypes are subtypes of the Built-in DataTypes. They are handled on the wire like the Built-in DataType, i.e. they cannot be distinguished on the wire from their Built-in supertypes. Since they are handled like Built-in DataTypes regarding the encoding they cannot have encodings defined in the AddressSpace. Clients can read the DataType Attribute of a Variable or VariableType to identify the Simple DataType of the Value Attribute. An example of a Simple DataType is Duration. It is handled on the wire as a Double but the Client can read the DataType Attribute and thus interpret the value as defined by Duration.

Structured DataTypes are DataTypes that represent structured data and are not defined as Built-in DataTypes. Structured DataTypes inherit directly or indirectly from the DataType Structure. Structured DataTypes may have several encodings and the encodings are exposed in the AddressSpace. The encoding of the Structured DataType is transmitted with each value, thus Clients are aware of the DataType without reading the DataType Attribute. The encoding has to be transmitted so the Client is able to interpret the data.

Enumeration DataTypes are DataTypes that represent discrete sets of named values. Enumerations are always encoded as Int32. Enumeration DataTypes inherit directly or indirectly from the DataType Enumeration. Enumerations have no encodings exposed in the AddressSpace. To expose the human-readable representation of an enumerated value the DataType Node may have the EnumStrings Property that contains an array of LocalizedText. The Integer representation of the enumeration value points to a position within that array. EnumValues Property can be used instead of the EnumStrings to support integer representation of enumerations that are not zero-based or have gaps. It contains an array of a Structured DataType containing the integer representation as well as the human-readable representation.

In addition to the DataTypes described above, abstract DataTypes are also supported, which do not have any encodings and cannot be exchanged on the wire. Variables and VariableTypes use abstract DataTypes to indicate that their Value may be any one of the subtypes of the abstract DataType.

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4.1.5 Standard Data Types

Name	Description
Boolean	This Built-in DataType defines a value that is either TRUE or FALSE.
Byte	This *Built-in DataType* defines a value in the range of 0 to 255.
ByteString	This *Built-in DataType* defines a value that is a sequence of Byte values.
DateTime	This *Built-in DataType* defines a Gregorian calendar date.
Double	This *Simple DataType* is a *Double* that defines an interval of time in milliseconds (fractions can be used to define sub-millisecond values). Negative values are generally invalid but may have special meanings where the *Duration* is used.
Float	This *Built-in DataType* defines a value that adheres to the IEEE 754-1985 single precision data type definition.
Guid	This *Built-in DataType* defines a value that is a 128-bit Globally Unique Identifier.
SByte	This *Built-in DataType* defines a value that is a signed integer between −128 and 127 inclusive.
Integer	This abstract *DataType* defines an integer whose length is defined by its subtypes.
Int16	This *Built-in DataType* defines a value that is a signed integer between −32 768 and 32 767 inclusive.
Int32	This *Built-in DataType* defines a value that is a signed integer between −2 147 483 648 and 2 147 483 647 inclusive.
Int64	This *Built-in DataType* defines a value that is a signed integer between −9 223 372 036 854 775 808 and 9 223 372 036 854 775 807 inclusive.
Number	This abstract *DataType* defines a number. Details are defined by its subtypes.
String	This *Built-in DataType* defines a Unicode character string that should exclude control characters that are not whitespaces.
UInteger	This abstract *DataType* defines an unsigned integer whose length is defined by its subtypes.
UInt16	This *Built-in DataType* defines a value that is an unsigned integer between 0 and 65 535 inclusive.
UInt32	This *Built-in DataType* defines a value that is an unsigned integer between 0

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	and 4 294 967 295 inclusive.
UInt64	This *Built-in DataType* defines a value that is an unsigned integer between 0 and 18 446 744 073 709 551 615 inclusive.
UtcTime	This *simple DataType* is a *DateTime* used to define Coordinated Universal Time (UTC) values. All time values conveyed between OPC UA *Servers* and *Clients* are UTC values. *Clients* shall provide any conversions between UTC and local time.
DateString	This *Simple DataType* defines a value which is a day in the Gregorian calendar in string. Lexical representation of the string shall conform to calendar date defined in ISO 8601-2000.
DecimalString	This *Simple DataType* defines a value that represens a decimal number as a string.
DurationString	This *Simple DataType* defines a value that represents a duration of time as a string. It shall conform to duration as defined in ISO 8601-2000.
NormalizedString	This *Simple DataType* defines a string value that shall be normalized according to Unicode
TimeString	This *Simple DataType* defines a value that represents a time as a string. It shall conform to time of day as defined in ISO 8601-2000.
Structure	This abstract *DataType* is the base *DataType* for all *Structured DataTypes*
IdType	This *DataType* is an enumeration that identifies the IdType of a *NodeId*.
Image	This abstract *DataType* defines a *ByteString* representing an image.
ImageBMP	This *Simple DataType* defines a *ByteString* representing an image in BMP format.
ImageGIF	This *Simple DataType* defines a *ByteString* representing an image in GIF format.
ImageJPG	This *Simple DataType* defines a *ByteString* representing an image in JPG format.
ImagePNG	This *Simple DataType* defines a *ByteString* representing an image in PNG format. PNG is defined in ISO/IEC 15948.
TimeZoneDataType	This *Structured DataType* defines the local time that may or may not take daylight saving time into account.
NamingRuleType	This *DataType* is an enumeration that identifies the *NamingRule*
NodeClass	This *DataType* is an enumeration that identifies a *NodeClass*.

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NamespaceIndex	The namespace is a URI that identifies the naming authority responsible for assigning the identifier element of the NodeId. Naming authorities include the local Server, the underlying system, standards bodies and consortia. It is expected that most Nodes will use the URI of the Server or of the underlying system.
IdentifierType	The IdentifierType element identifies the type of the NodeId, its format and its scope.
Identifier value	The identifier value element is used within the context of the first three elements to identify the Node. Its data type and format is defined by the IdType.
QualifiedName	This Built-in DataType contains a qualified name. It is, for example, used as BrowseName.
LocaleId	This Simple DataType is specified as a string that is composed of a language component and a country/region component as specified by IEEE 754-1985, IEEE Standard for Binary Floating-Point Arithmetic
LocalizedText	This Built-in DataType defines a structure containing a String in a locale-specific translation specified in the identifier for the locale.
Argument	This Structured DataType defines a Method input or output argument specification. It is for example used in the input and output argument Properties for Methods.
BaseDataType	This abstract DataType defines a value that can have any valid DataType. It defines a special value null indicating that a value is not present.
Enumeration	This abstract *DataType* is the base *DataType* for all enumeration *DataTypes* like *NodeClass*
XmlElement	This *Built-in DataType* is used to define XML elements.
EnumValueType	This *Structured DataType* is used to represent a human-readable representation of an Enumeration.
OptionSet	This abstract *DataType* is the base *DataType* for all *DataTypes* representing a bit mask.
Union	This abstract *DataType* is the base *DataType* for all union *DataTypes*. The *DataType* is a subtype of *Structure DataType*.

Table 8: Standard data types

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4.2 Acquisition of data

4.2.1 Smart Sensor network and offline measurement

The Smart Sensor Network (SSN) comprises of sensors for a) monitoring the states of machines and the fluency of production (machine status), b) observing the activities, states and location of workers (worker status), as well as, c) observing the properties of the working environment (context).

The machinery involved in the industrial use cases of Prima Power and Continental collect data regarding the behavior of machines through inherent tracking mechanisms. These data will be utilized to monitor the status of machines and production.

Personal tracking devices from the well-being consumer market will be utilized for observing worker status. These will include the Fitbit Charge 2 wristband and the Samsung Gear S3 smartwatch for measuring a) activity in terms of steps and the intensity of physical activity, b) heart rate including also heart rate variability and resting heart rate, and c) sleep in terms of the amount and quality. In addition, the Moodmetric ring for sensing the emotional intensity of the worker (e.g. high stress or excitement) will be considered, but since wearing a ring during manufacturing work is quite impractical and might pose even safety issues, it might not be a viable option. See D1.1. *Enabling technologies* (Chapter 6) for a more detailed description of these devices.

There are several environment sensors available in the market for monitoring context. Below, a few of these are introduced for consideration in Factory2Fit:

- Omron Environment Sensor [30] measures humidity, temperature, noise, light, and air pressure
- Bosch Sensortec [31] measures air quality (gas), humidity and temperature
- Eaton Environment Sensor [32] measures humidity and temperature

4.2.2 Interactive data logging tool

For the determination of the worker's status and the interaction between worker and machine/factory, TUC is testing the Samsung Gear S3 frontier. In lack of preinstalled apps for this specific usage, a new application for the Samsung Gear S3 and one for Universal Windows Platform (UWP) has been developed. The intention is to have an application for the Samsung Gear S3, which retrieves information from the device's sensors, e.g. moving status or localization. This data is send via Bluetooth to a laptop running UWP and is logged there. Moreover, the two apps can communicate with each other in a way that arbitrary information (e.g. about the status of the machine or requests from foreman) can be send to the Samsung Gear S3 either once by clicking a certain button or by sending continuously updated information by selecting the corresponding option. Some messages can be answered by selection of different response options. This can be used for answering simple questionnaires with the Samsung Gear S3.

The application on the Samsung Gear S3 is designed in the "Tizen Advanced UI" (TAU) which is provided by the operating system of the S3 called "Tizen", used by Samsung to run their wearables.

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After opening the app, the user sees a start page, on which a button can be touched to start an experiment (Figure 4: “Welcome to Factory2Fit! Choose one of the following options: - Start experiment - Debug”).

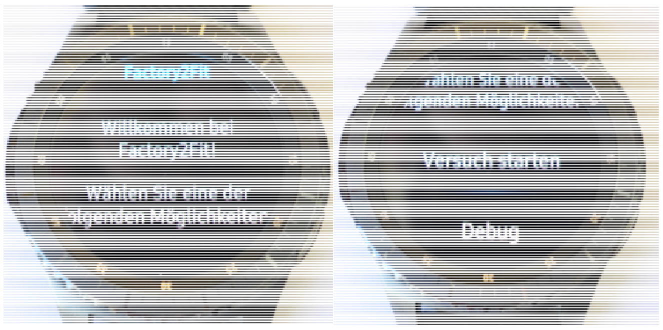
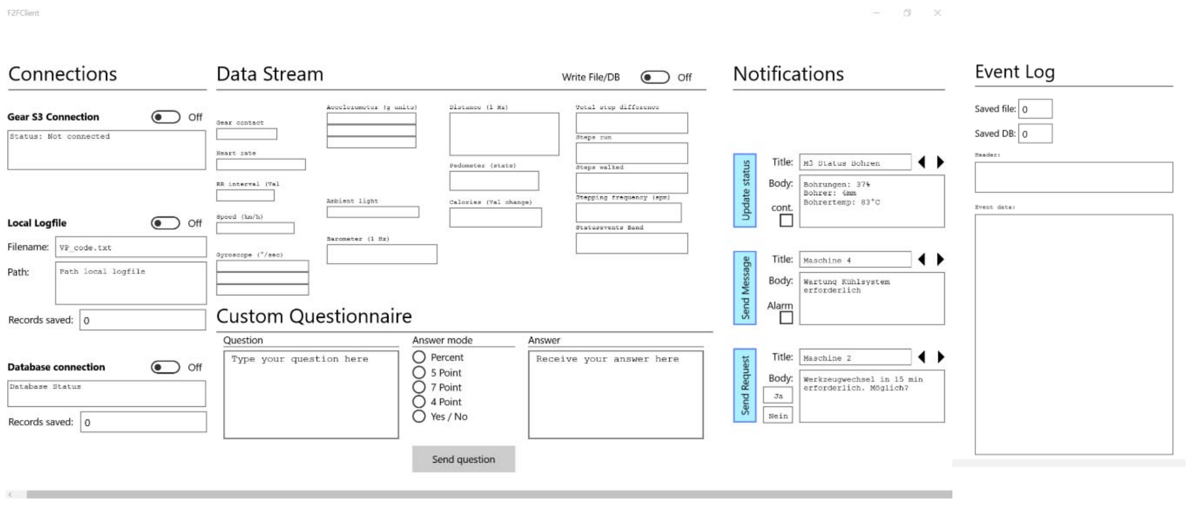

Factory2Fit
Willkommen bei Factory2Fit!
Wählen Sie eine der folgenden Möglichkeiten
Versuch starten
Debug

Figure 4: Start page of the Samsung Gear S3 app

Touching this button leads to the initialization page. While this page is shown, the needed Bluetooth services are registered, so the UWP-app can connect afterwards. After touching the “Continue” button, the user sees a blank page, on which the “Update Status”-message is displayed, as soon as it is sent by the UWP-app.

After opening the UWP app the user interface shown in Figure 5 can be seen. The Interface of this app is divided into the sections “Connections”, “Data stream”, “Custom Questionnaire”, “Notifications”, and “Event Log”.



F2FClient

Connections

Gear S3 Connection Off
Status: Not connected

Local Logfile Off
Filename: VP_code.txt
Path: Path local logfile
Records saved: 0

Database connection Off
Database Status
Records saved: 0

Data Stream

Write File/DB Off

Gear contact
Heart rate
RR interval (Val
Speed (km/h)
Gyroscope (°/sec)
Accelerometer (g units)
Ambient light
Barometer (1 Hz)
Distance (1 Hz)
Pedometer (state)
Calories (Val change)
Total step difference
Steps run
Steps walked
Stepping frequency (spm)
Statusevents Band

Custom Questionnaire

Question: Type your question here
Answer mode: Percent / 5 Point / 7 Point / 4 Point / Yes / No
Answer: Receive your answer here
Send question

Notifications

Update status
Title: M3 Status Bohren
Body: Bohrungen: 37%
Bohrer: 4mm
Bohrertemp: 83°C
cont. ☐

Send Message
Title: Maschine 4
Body: Wartung Kühlsystem erforderlich
Alarm ☐

Send Request
Title: Maschine 2
Body: Werkzeugwechsel in 15 min erforderlich. Möglich?
Ja
Nein

Event Log

Saved file: 0
Saved DB: 0
Header:
Event data:

Figure 5: Overview of the UWP-app.

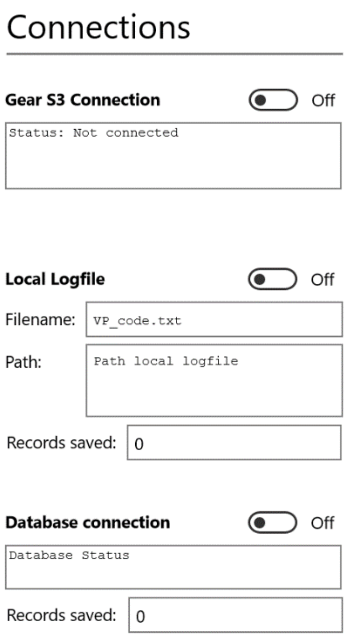
The Section "Connections", as shown in Figure 6, is further divided into the three subsections "Gear S3 Connection", "Local Logfile" and "Database connection". Each of them contains a toggle switch and one or more textboxes to display specific information.

The "Gear S3 Connection" subsection is used to establish the connection to the corresponding app on the Samsung Gear S3. To be successful at doing so, the app on the Samsung Gear S3 must already be running and navigated to the initialization ("Initialisierung") page. Otherwise trying to toggle the switch in this section will result in an error message.

The "Local log file" subsection is used to name and create the log file into which the continuously received data from the S3 are written. The current path of the log file is displayed in the "Path" labeled textbox.

The "Database connection" subsection is used to connect to a SQL database and save the recordings directly into it.

The "Records saved" textbox displays the number of lines written to the log file or the database.



Connections

Gear S3 Connection — Off

Status: Not connected

Local Logfile — Off

Filename: VP_code.txt

Path: Path local logfile

Records saved: 0

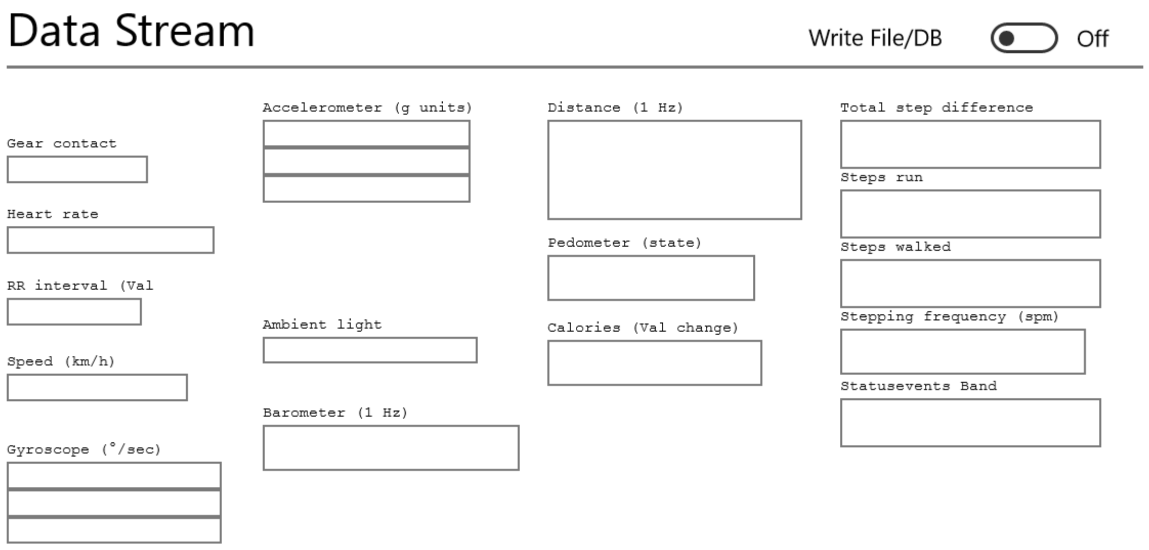
Database connection — Off

Database Status

Records saved: 0

Figure 6: *Connections section*

The section "Data Stream" contains one toggle switch (Figure 7), which is used to activate the collection of data sent by the watch. It also contains several textboxes in which the last read data set is displayed. The data stream include data like interheartbeat interval (RR interval, not available,



Data Stream

Write File/DB — Off

Gear contact

Heart rate

RR interval (Val

Speed (km/h)

Gyroscope (°/sec)

Accelerometer (g units)

Ambient light

Barometer (1 Hz)

Distance (1 Hz)

Pedometer (state)

Calories (Val change)

Total step difference

Steps run

Steps walked

Stepping frequency (spm)

Statusevents Band

yet), state of movement (pedometer state), total steps per recording (Total step differences).

Figure 7: *Data Stream section*

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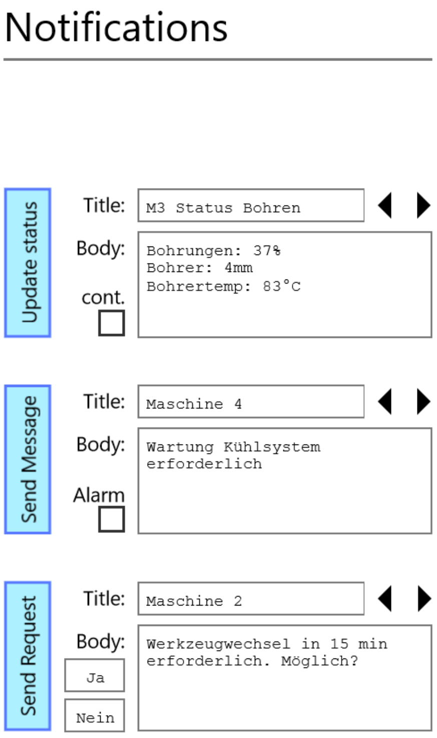
This section is being refreshed approximately every 100 milliseconds. This corresponds with the measuring rate of the heart beat and the RR interval. To display data here, the continue button on the Gear-app's initialization page must have been pressed already.

The section "Notifications" (Figure 8) is used to send three distinct kinds of short messages to the Samsung Gear S3 app, after the recordings have been started. The feature "Update status" sends a plain text message with a title and a body to be displayed on the watch. If needed, the update can also be sent continuously by checking the "cont." checkbox.

The "Send Message" subsection is used to send a message to the watch, which has to be manually accepted by the user of the smartwatch.

The "Send request" subsection is used to send a request to the user, which can be answered with yes or no. The received answer is then shown in the corresponding textbox in the UWP app.

In Figure 9, the representation of the three message types on the watch is shown.



Notifications

Update status

Title: M3 Status Bohren

Body:
Bohrungen: 37%
Bohrer: 4mm
Bohrertemp: 83°C

cont. ☐

Send Message

Title: Maschine 4

Body:
Wartung Kühlsystem
erforderlich

Alarm ☐

Send Request

Title: Maschine 2

Body:
Werkzeugwechsel in 15 min
erforderlich. Möglich?

Ja

Nein

***Figure 8**: Notifications section*

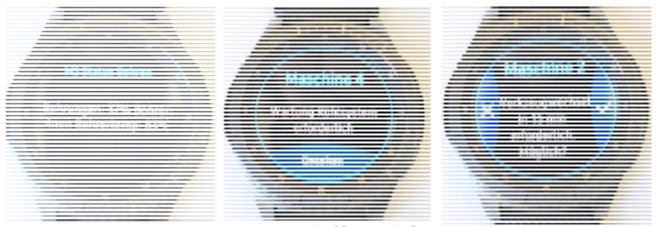


***Figure 9:** Messages on the watch (from left to right: Update, Message, Request)*

4.3 Data storage, retrieving and distribution in a factory

4.3.1 Description of the architecture for online measures and offline data

The overall Factory2Fit functional architecture can be seen in Figure 10, as previously defined in D1.4, *Adaptation Architecture* (Dissemination Level: Confidential). As can be seen in this Figure, the Factory2Fit Repository, a central Knowledge Base containing all data concerning the factory floor, is placed at the centre of the architecture. The Smart Sensor Network Online measures and monitoring module is responsible for either feeding in data directly to the Factory2Fit Repository or propagating it through the Advanced Modelling Tools. The Quantified Worker approach is a component of the *Contextual Analysis and Semantics* Layer, being directly fed input from the smart devices, that can either be smart bands, or smart watches. Internally, the module will provide components for monitoring sensors on machine status, worker condition and context.

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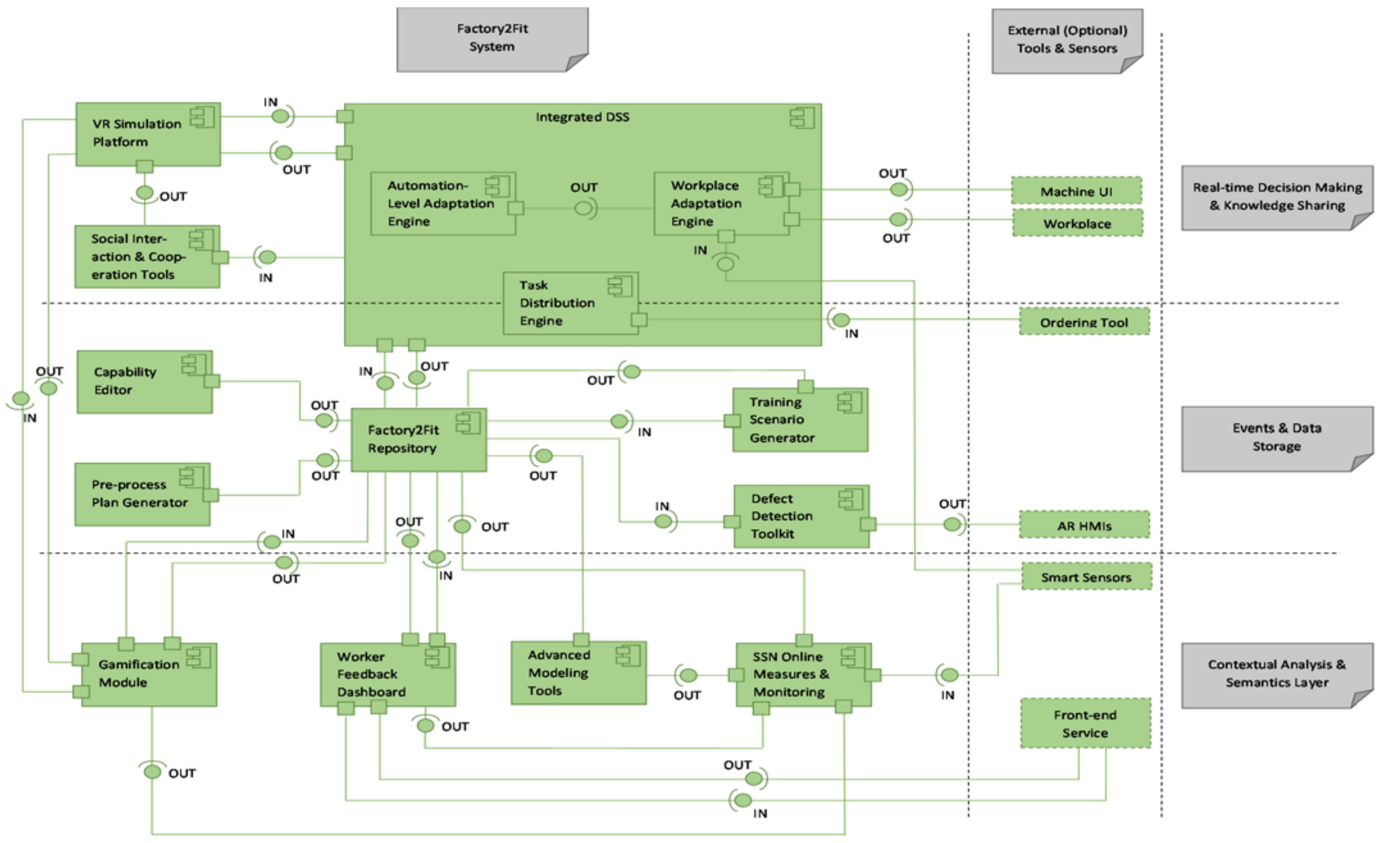
Factory2Fit System
External (Optional) Tools & Sensors
VR Simulation Platform
Integrated DSS
Automation-Level Adaptation Engine
Workplace Adaptation Engine
Task Distribution Engine
Social Inter-action & Coop-eration Tools
Capability Editor
Pre-process Plan Generator
Factory2Fit Repository
Training Scenario Generator
Defect Detection Toolkit
Gamification Module
Worker Feedback Dashboard
Advanced Modeling Tools
SSN Online Measures & Monitoring
Machine UI
Workplace
Ordering Tool
AR HMIs
Smart Sensors
Front-end Service
Real-time Decision Making & Knowledge Sharing
Events & Data Storage
Contextual Analysis & Semantics Layer
IN
OUT

Figure 10: Factory2Fit overall functional architecture component diagram (retrieved from D1.4).

Additional components related to the acquisition and storage of data for offline data acquisition are represented in the *Events & Data Storage* Layer, namely the Capability Editor and the Pre-process plan generator. Both modules serve the purpose of structuring (in a common representation format) the data needed for the adaptation. The latter is based on capability coarse matching followed by a holonic negotiation process to fuel the actual reasoning on matching resources and workers to product requirements. The output of both modules is stored on to the Factory2Fit Repository. Additional information on these modules can be found in D1.4, *Adaptation Architecture*, as well as a detailed overview on the implementation of the actual modules and their interfaces will be delivered in D3.1, *Adaptation features and modules* (Dissemination Level: Confidential).

4.3.2 Data storage concept of Factory2Fit

Factory2Fit repository will be a central database per use case which will be responsible for storing both static and real-time dynamic information acquired from various heterogeneous sources in the shop floor and smart sensors, in a uniform way. The benefits of a centralized data storage system are

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multiple. In central data storage systems it is easier to store and handle large scale data, have closer control and protection of the data.

The central data storage will contain both static and dynamic information about the shop floor, procedures, data from smart sensors, equipment related to the project, pre-process plan, factory resources' blueprints, installed sensors, Augmented Reality devices used in operational situations, etc. The repository also stores information created by other software modules, such as the *Pre-Process Plan Generator*, the *Capability Editor* and the *Advanced Modelling Tools*. All these information has been translated and presented in a common understandable format, so as all Factory2Fit components can efficiently and unobtrusively use them.

The design of the repository was mainly determined by the information required from the Factory2Fit components that can be generated only as a combination (and/or modification) of particular models. The Factory2Fit components will request information from the repository using web services to retrieve or to save data. All the web services will use a composition of different elements of the repository for information exchange. As mentioned in Factory2Fit deliverable D1.4, *Adaptation Architecture* [20], each module will be responsible for querying the repository through built-in web services, to instantiate communication, request and receive data, as well as send it back for future storage. Thus, a repository's web service can be called from various different modules. The modules should be able to process the information returned which will be in the common format (e.g. JSON). Similarly, when a module uploads data for storage in the repository, the corresponding web service must be called and the input must comply with the common format. Through the use of the repository's web services, the different Factory2Fit modules are able to store and retrieve data transparently, without the need to interact directly with the database engine which is installed, or have any information about the internal structure of the database. Furthermore, the use of a unified API allows complex Factory2Fit components to retrieve information derived from different modules without the need of integrating a different API per information source.

For the implementation of the central database, Structured Query Language (SQL) could be used. SQL is a language with multiple advantages, such as improved accessibility, independence and efficiency. SQL can also handle large amounts of records and supports the use of relational databases which can better handle large amounts of distributed records. MySQL database [21] is a popular, scalable and reliable SQL database which can be considered for the actual implementation. Additionally, a hybrid database solution can be adopted. According to the hybrid approach, the Factory2Fit repository can utilize two different database technologies: an SQL based and a NoSQL [22] database, such as InfluxDB [23] or MongoDB [24]. Due to the fact that Factory2Fit sensor network handles real-time data from various sensor types, these type of data can be stored in such a NoSQL database which offers much higher performance when retrieving the data compared to a SQL database.

Another method for data exchange between the different modules is the use of the publish/subscribe approach which is realized by the MQTT [25] protocol. The MQTT protocol is a lightweight messaging protocol for small sensors and mobile devices. The protocol uses a publish/subscribe architecture in contrast to HTTP with its request/response paradigm. Publish/Subscribe is event-driven and enables messages to be pushed to clients. The central

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communication point is the MQTT Broker, it is in charge of dispatching all messages between the senders and the rightful receivers. Each client that publishes a message to the Broker, includes a topic into the message. A topic is a simple string that can have more hierarchy levels, which are separated by a slash and it is the routing information for the broker. Each client that wants to receive messages subscribes to a certain topic and the broker delivers all messages with the matching topic to the client. Therefore the clients don't have to know each other, they only communicate over the topic. This architecture enables highly scalable solutions without dependencies between the data producers and the data consumers [26].

Factory2Fit module includes an MQTT client, which will apply the connection with the MQTT Broker, which acts as server. By subscribing to the corresponding topic of the MQTT Broker, a module can receive a new event that has been published to the same topic by another Factory2Fit module without the need to query the repository's web service. An MQTT aggregator module can be used in order to store the MQTT published events into the repository using the web services defined. In this way the events that are sent via the MQTT protocol can be available as historical data through the repository.

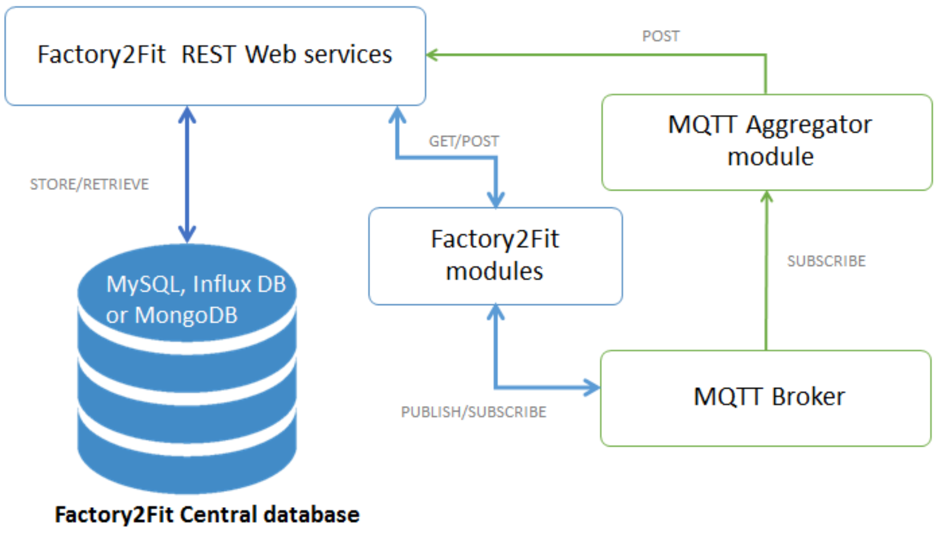

Figure 11: Factory2Fit Central data storage architecture

Although, Factory2Fit module can also get or post an event to the Factory2Fit database, through a Web service without the need for communication with the MQTT Broker. In case of exchanging real-time data among different modules, such as data acquired from sensors, the MQTT Protocol offers low-response acquisition of real-time events due to the publish/subscribe model. To define if the data will be stored directly to the database through a web service, or the MQTT Broker and MQTT aggregator module, a flag that will define the course that will be followed can be set.

Seeing how many of the modules defined in D1.4 designate "Web Services APIs" for communication with the Factory2Fit Repository, and also taking into account the need for efficiency and stale data protection, we propose the use of a Falcor – based middleware, in addition to the former mentioned architecture. Falcor can guarantee efficient client/server interactions and also supports protection from duplicate data with the use of a JSON Graph. It will allow modelling of all factory back-end data as a single JSON resource on the repository, allowing clients to request subsets of this resource on demand, just as they would from an in-memory JSON object, but in an asynchronous manner. This has the potential of greatly simplifying the APIs, as knowledge of the actual data infers knowledge of the API. The model allows developers to create a virtual server JSON model, which can be transparently accessed from any connected device. Furthermore, the asynchronous nature of Falcor allows for extended flexibility in moving the data anywhere on the network as the client code consuming the data can remain completely unchanged.

Falcor [33] is an innovative JavaScript library for efficient data fetching. It allows developers to model all backend data as a single Virtual JSON object on a Node server. Consequently, on the client, developers are free to work with the remote JSON object using standard JavaScript operations. Falcor is middleware; therefore it is not a replacement for application servers, databases or MVC frameworks. Instead, Falcor can be used to optimize communication between layers of new and/or existing applications. Falcor was developed, and is the data platform that powers the User Interfaces of streaming media and video-on-demand giant Netflix.

Falcor enables remote data representation in a single domain model called a JSON Graph. The latter is a data representation that allows modelling graph information as a JSON object, which can be parsed by a typical JSON parser. JSON is a ubiquitous data interchange format, which is often used by applications for data exchange due to the ease of manipulation of JSON objects in JavaScript. JSON is map-based, making it easier to split large data sets into smaller subsets and send them across the wire on demand. Typical JSON however models trees, while most application domains are graphs. This introduces a problem, as the serialization of a graph into JSON format can introduce duplicate copies of the same entity. Not only do these entities acquire additional space when sent across the wire, but they also risk creating stale data. Stale data occurs when changes are made to one instance of an entity but they are not propagated to the other instances, risking users being presents different instances of the same entity, rather than the one changed.

To avoid this problem, developers often remove duplicates by assigning a unique identifier to the entity, so that the client can detect duplicates before they are added to the cache. This often requires the writing of custom code for each new type added to the system. Falcor's JSON Graph addresses this shortcoming in the JSON format by allowing a graph to be modelled as JSON without introducing duplicates. It also provides a set of abstract operations that allow applications to retrieve all the data required in a single round trip, dramatically reducing latency. Using JSON Graph, developers can retrieve data from a virtual server model the same way they would from an in-memory JSON object.

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5 Conclusions

The main intention of this deliverable was to provide a list of potential measures to describe quantitatively the workers, tasks, and context within a factory. The online measures and offline data are directly derived from the characteristics and the variables of the Adaptive Worker Model described in Deliverable 2.2, *Dynamic Worker Model*.

Especially, the quantification of the worker is based on a new approach, the *quantified worker approach*. This aims toward the adaptive implementation of the workers into factory processes as well as developing self-understanding through personal feedback. To describe the data collection of the relevant information, a definition of online measurement and offline data collection, suitable for the Factory2Fit framework was developed.

The gathered parameters include possible measures and information, that are useful to describe the workers status, tasks, and context, but might not all be included in the three industrial pilots. Furthermore, it is emphasized that ethical aspects need to be taken into account, like what data will be collected and how it will be used while at the same time, securing the privacy of the worker.

The concepts of the use cases that are going to be realized are described in this deliverable and a first draft of relevant measures and parameters is presented. In month 22 of the Factory2Fit project, the list of measures in deliverable will be updated and matched with the parameters actually used in the pilots. Beforehand, the measures will be validated in Task 2.4, *Validation of the user model* and the techniques to acquire the data will be tested.

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