trinity ENGAGE WITH AGILE MANUFACTURING

D3.4. Report on metrics for validation and results of internal demonstrations

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PP	Restricted to other programme participants (incl. Commission Services)	
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1 Introduction

The main aim of this deliverable is to report the metrics for validating the internal use case demonstrations. The metrics is used to characterize the performance of the systems and subsystems developed internally in WP3 on quantitative grounds and to identify the weakest points and potentially critical KPIs for the manufacturing solutions. Using the results of this evaluation analysis, we will provide guidelines for the improvement of the potential industrial systems and guide a cross-fertilization process leading to integrated solutions.

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2 About Key Performance Indicators

Key Performance Indicators (KPIs) are the critical key indicators of progress toward an *intended result*. KPIs provides a focus for strategic and operational improvement, create an analytical basis for decision making and help focus attention on what matters most. As Peter Drucker famously said, "What gets measured gets done." (kpi.org) The intended result can be expressed in the form of a goal. When defining the goals, the SMART -model can be used to help creating good, articulated goals:

- **S**pecific: Define what you want to achieve
- **M**easurable: What indicates that you have reach your goal?
- **A**chievable: Is the set goal attainable?
- **R**elevant: Is the goal relevant for you? Does it align with where you want to be?
- **T**ime-bound: When will we have achieved the set goal?

Good articulated goals can be characterized as being a single statement, SMART, and outcome based. An example of a SMART goal could be:

"We will have a remote programming environment in use by end of June 2022"

- Specific: the programming environment is separated from physical assets
- Measurable: we can determine that the environment is live and functioning
- Achievable: even though the goal is ambitious, we already have a good portion of the environment in place and only the final touches are needed
- Relevant: Remote working is emphasized in the world these days, as the pandemic times demonstrated that remote working can be efficient and realistic. It can be beneficial in future, without pandemic restrictions
- Time-bound: The milestone for the release is set to June 2022

Earlier we defined the KPIs as key indicators of performance towards an intended result or a goal, so it is important to set the KPIs to measure the things that contribute to the realization of the goal. It is also worthwhile to think, whether the intended result can be measured directly, or is it something that can be captured with several measurements. Each goal needs its own KPIs to monitor and measure success.

Some characteristics of a good KPI:

- it provides objective evidence of progress towards the desired result stated in the form of an articulated goal
- it measures what is intended to be measured
- It has a target for the measurement
- it gauges performance over time
- It has a solid data source that can be defined

When evaluating performance over time, it is useful to use thresholds for the target to tell whether you are doing good or bad with the measurement.

Here are some examples of different KPI basic types:

- Raw numbers: "number of new customers"

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- Progress: "% of completion%
- Change: "% increase in sales"
- Ratios: "cost per new customer lead"

Example of a Goal / KPI set
- Goal: We will increase our sales by 25% during 2022 (this is our desired outcome, it uses the SMART framework, and it is a single statement)
    - KPI 1: We have acquired 1000 new customers by the end of 2022 (quantifiable, it has a timeframe, we can use the CRM as data source, and we can measure this monthly)
    - KPI 2: We have increased our up-selling rate by 15% by H1/2022 (quantifiable, it has a timeframe, we can use the CRM as data source, and we can measure this monthly)

2.1 KPIs in the manufacturing domain

The most common KPIs in the manufacturing domain are either technical or economical. The downside of these is the fact that they can only measure things that are in numbers. This means that softer, human related indicators might not be accounted for. Historically the comparison of various KPIs has been difficult due to the varying interpretations of the measurements and indicators. The paper[1] aims to define a set of indicators and sustainability metrics that are needed in the manufacturing domain. These indicators are then used to measure the performance of our use cases. The categorization of the KPIs was done according to the four categories presented in the paper.

Sustainability in manufacturing can be measured in four categories:
- Social sustainability
    - Human capital is the main enabler of the Factories of the Future
    - Human skills and engagement to manufacturing will determine the manufacturing development of Europe
- Technical sustainability
    - Used to maintain current and develop future behavior and characteristics of the environment, both on real and virtual existences
    - Can offer great value for decision-making
        - Divided into manufacturing process monitoring, manufacturing flow efficiency and competence of the company
- Economic sustainability
    - Seeks to secure both short and long term profitability and economic viability
    - The ability to produce and provide products that meet the needs of customers in a profitable way plays a key role in economic sustainability
    - Most are related to costs with the aim of cost-reduction
- Ecological sustainability
    - Focus is on waste and carbon emissions, conservation of energy and natural resources
    - Sustainable manufacturing consists of:
        - Manufacturing sustainable products
        - Manufacturing all products using sustainable practices

[1] M Lanz, E Järvenpää, H Nylund, R Tuokko, S Torvinen, K Georgoulias, Sustainability and performance indicators landscape, proceedings of International Conference on Flexible Automation and Intelligent Manufacturing (FAIM), 2014, pp. 283-290

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Table 1 KPIs identified within our Use Cases

KPI metrics	UC1	UC2	UC3	UC4	UC5	UC6	UC7	UC8	UC9	UC10	UC 11	UC12	UC13	UC14	UC15	UC16	UC17	UC18
Technical KPIs (technical scalability of system, improvement of quality, improvement of speeds, efficiency, reduction of machine errors...)																		
Set-up time reduction: percentage of time reduced comparing with previous solution					X		X										X	
Re-configure time: compare the time it takes to re-program or re-setup a new product					X		X		X			X	X	X				
Cycle time: Time it takes to perform one cycle of operation from start to finish. The operation may be the full order-delivery cycle or a single process operation. It should include the waiting steps that are part of the process.	X	X					X		X		X					X	X	
Throughput rate: Amount of jobs done in time unit	X	X						X			X					X		
Production lead time (Throughput time): from start of manufacturing to final product (including testing))			X															
Set-up time: Amount of time needed for setting up the machine including change of tools, fixtures, programs etc.			X				X	X	X	X		X	X		X	X		X
Training time: Production time saved with concurrent training								X		X				X			X	
Technology swap feasibility: Percentage of components (HW&SW) that can be swapped without major changes to other components							X							X				
Environmental KPIs (reduction of energy consumption, reduction of material waste, reduction of poor quality products...)																		
Energy Consumption											X							
Energy Cost																		
Energy Efficiency								X										
Materials used by weight or volume			X															
Social KPIs (educational, skills upgrade, re-skilling, reduction of human errors....)																		
Labor safety: percentage of human labor removed from hazardous environment	X	X	X				X	X	X					X				
Accessibility: level of open source-based software						X	X			X					X			X
Easiness in application: time from idea to operation								X				X						X
Training costs	X	X		X						X				X				
Economic KPIs (incl. Lean reduction of waste originating from 8+1 waste)																		
Reduction of waiting time for human operators, parts and products									X							X		
Reduction of transportation time of parts and products																		
Reduction of transportation time of tools																		
Cost-efficiency: reduce the time of operators traveling						X								X				
Cost-efficiency: reduce the number of operator, one operator can control multiple robots	X	X				X	X	X										
Cost-efficiency: reduce the cost by using the robot instead of manual work	X	X				X		X								X		
Cost-efficiency: reduce the cost of ownership (set-up, operational cost, maintenance, etc.)					X			X										X
Direct economic value generated and distributed, including revenues, operating costs, employee compensation, donations and other community investments, retained earnings, and payments to capital providers and governments.				X														
Labor																		
Type of injury and rates of injury, occupational deceases, lost days, and absenteeism, and total number of work-related fatalities by region and by gender														X				

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3 Improvement of potential industrial systems

3.1 Responding to the challenge of availability of workforce and special skills

It can be generalized that the access and availability of personnel with specific high-tech knowledge can be limited for industrial companies. This means that there might not be a specialist available to engineer and implement the potential new automation systems or technologies in use. This is quite often the reason to seek for an automation integrator that can take the technologies in use or implement even a complete system or cell level solution. Several use cases identified that it is beneficial to improve the solutions to be based more on open-source technologies and standardized interfaces, thus enabling easier applicability with the internal engineering teams at the end customer (UC#10). It is quite typical, that companies have limited robotics know-how, which in turn makes it more difficult to apply customized robotic solutions. Several use cases had identified that this challenge could be improved by creating novel user interfaces that support the application of the technologies. An example of such user interface would be graphical programming wizards to program robots (UC#6, UC#7, UC#8, UC#12, UC#13). This way one does not have to be a robot specialist to generate robot programs. Another example is the use of innovative user interfaces for human interaction with the robotic and automation systems (UC#10).

3.2 Regulations governing machinery

In the European Union, the machinery directive sets the ground rules for applying technologies to form machinery. When the end user is applying robotics and technologies to form a robotic solution, one of the key questions is, when does the user become a machine supplier. This is a very important question from the perspective of the responsibilities and the requirements associated to these roles. This is also one reason why customers often seek for partners that take care of the integration and the associated requirements of the regulations. One improvement to the applicability of the TRINITY use case technologies could be to provide a set of pre-made documentation that supports the integration process and covering the needed regulations. Examples of such documents could be a pre-made risk analysis template for the technologies, or a Process Failure Mode & Effects Analysis providing keyways to eliminate process related shortcomings of the integration of a given technology.

3.3 Industrial users benefit from longer life-cycle support

Investments to industrial machinery are usually made for several years, even decades. During this period the support of the used technologies plays a big role. Some industrial users request for spare parts availability for 10-15 years. Against this background it would be essential for the TRINITY use cases to be based on technologies that are created based on standards, as this enables, at least to some extent the possibility to find support for the proposed technologies also in the next 5-10 years.

Another aspect of life-cycle support is the possible limitation of the technology stack that the customers are willing to apply. As an example, if the customer already has robots from one vendor, it might be a difficult journey to try to convince a change to an alternative robot vendor. This challenge has been addressed in many of the proposed improvements as the target to increase the amount of suitable HW providers (UC#7, UC#10, UC#12, UC#17), or implementing more standard interfaces.

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3.4 Estimating the payback

The payback of the investment will be determined on how well the intended result will realize. In the end, the analysis will be made End-To-End, from the start of the implementation of these new technologies up to the end, when the system is being used and it is producing and generating value. This includes also the effort required to integrate and program the system, as well as the effort it takes to use and support it. Thus, it is important to make sure that the proposed technologies would be easy to approach and integrate, and that they would be well supported. Any investment that is constantly off-line due to missing personnel know-how or lacking spare parts does not produce the intended return on investment. Several use cases had also identified performance related improvements such as system cycle time (UC#9, UC#11, UC#18), energy consumption (UC#11), and reprogramming time (UC#5, UC#8, UC#9 UC#12, UC#13, UC#15, UC#17, UC#18) as solutions that would contribute to an improvement in output and ROI.

3.5 The DAP and TRINITY-network helps in planning of the applications

The expectations for the result of the integration of technologies are often optimistic and there might not be a clear understanding of the limits or costs of the technologies. As an example, it might be a defined requirement that a bin-picking solution would achieve 100% emptying grade of the material container, as no manual material handling is allowed. But many times, it is these extreme ends of the requirements that tend to raise the price tag of the integration to great extent, and this can come as a surprise to many. Many of the demonstrators and use cases presented by the TRINITY consortium are novel technologies, and they represent lower TRL levels at this stage (UC#5&6: TRL4-5; UC#7: TRL5-6; UC#8: TRL4; UC#9: TRL5-6; UC#10: TRL5-6; UC#11: TRL5; UC#12, UC#17: TRL4-5; UC#13: TRL4-5; UC#16: TRL 4-5; UC#18: TRL5-6). The TRINITY DAP and the associated network offers information and services related to the integration and application of these modules and technologies, so that the outcome of the investment can be safely planned and taken into use with realistic expectations.

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4 Cross-fertilization of demonstrators and technologies

One of the original ideas of the cross-fertilization concept was to enable the TRINITY consortium to cross-use the technologies and modules developed during the project to form new use cases and complement the existing ones with possible new functionalities. However, direct applicability has been challenging as applying the modules greatly benefit from access to direct guidance of the module creators. On the other hand, a product-like, off-the-shelf module is also not expected as the modules are of lower TRL levels. The use cases also vary quite a lot between each other further complicating the cross-fertilizing of new use cases stemming from the modules.

4.1 Cross-fertilization amid COVID-challenges

The outbreak of COVID-19 impacted our ability to carry-out the most efficient means of cross-fertilization – joint working together directly on the demonstrators at the beginning of the project. The consortium was able to organize some researcher exchange despite the challenging travel situations. This provided some opportunities to work together on the modules. As an example, this kind of exchange took place between the partners TAU and Flanders MAKE. Internal deep-dives, both virtually and on-premise have been carried out as substitutions for researcher exchange. In these sessions it has been possible to discuss and spread information about the modules and discuss the applications of the technologies.

4.2 External cross-fertilization through the Open Calls

The Open Call approach also provided further opportunities to get feedback and new ideas on the application of the modules and technologies. As the potential use of TRINITY modules was also built into the evaluation criteria for the Open Call demonstrators, there was a good base to expect some applications with the modules in use. COVID-19 also impacted the on-site collaboration in the Open Call demonstrators, especially for during the first demonstrator program.

Examples of successful external cross-fertilizations can be found from the projects AGILE and ICON from Open Call 1, and SpinEye from Open Call 2. The AGILE project used the object detection module by EDI. It was used to determine the part picking pose from a tray with several parts and part types. The AGILE project was able to meet the set KPI for the picking cycle times, and the results were also jointly published in a journal. The ICON project used 3 TRINITY developed modules to complement the use cases with new functionalities through the modules. The ICON demonstrator was about agile electric motor manufacturing and in their final report they state that the system got new collaborative skills through safe human detection, projector-based user interface, and object classification features. The SpinEye project used the Object Detection Module by EDI, which is used to sense the changing environment and adjust the system's actions accordingly. This module is entirely responsible for detecting and accurately locating the screw holes where potential screws are to be mounted and thus forms an integral part of the SpinEye application.

Some projects tried to use TRINITY modules but found out that they were not suitable for the demonstrator applications for practical or commercial reasons. For example, such try-outs happened in the projects PROTON Robots, Aurora, and Brilliant, all from Open Call 2. Even though the modules might not have been a 100 percent match for the applications, they provided valuable insight of the application in general. This was the case with the PROTON robots project, where they tested and tried the UWB module from Flanders MAKE and, in the end, ended up using another technology. Even though the TRINITY module was not used in the end, it provided the information on how to fine tune and validate the requirements for

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the UWB requirements for the project. In project Brilliant the reasoning for not using the TRINITY object detection module was a practical one. The parts needed to be accurately picked with a two-finger gripper and inserted into an alignment jig, which was not feasible with the approach using the TRINITY module. These findings are also valuable to the TRINITY module owners, and they provide further information about the industrial applicability of the modules and possible improvement ways for the future.

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Appendix A: Key Performance Indicators in Use Cases

This appendix summarizes the identified key performance indicators in the TRINITY use cases. Each use case has its own chapter where the use case is described briefly, and the indicators and the respective definitions and measurements are described and quantified. Each use case is also analyzed for further improvements.

A.1 Use-Case 1: Collaborative assembly with vision-based system

Human-robot interaction for collaborative manufacturing requires special attention for HRI safety systems since robots and payloads can lead to potentially dangerous situations. We introduce a safety model that creates a dynamic 3D map of the working environment and at the same time ensures minimum safety distance between the human and robot. The model is created, updated and monitored using a single depth sensor. In addition, a projector is installed on top of the work environment and robot safety zone and virtual user interface components are projected onto a flat surface to increase the human awareness during the task.

Violation Detection success rate (DSM)

Verbal definition of KPI: The KPI will represent the robustness of system regarding detection of violation successfully.

Way to measure KPI and data source: A program will be defined to violate hazard area for ~8000 cycles. Two robots will be synchronized to store of time and number of actual and detected violation numbers.

Quantitate KPI: Success Rate was estimated to be 99.97%

Response Time (DSM)

Verbal definition of KPI: The KPI will represent how fast we can move through the safety zone such that the system still detects violation.

Way to measure KPI and data source: Robot performs linear motion between two points at different speeds such that its trajectory intersects with safety border. The speed at which the violation is not detected defines the KPI.

Quantitate KPI: The robot speed was limited to 500mm/s, at which violation is still detectable, although not as consistently. Therefore 500mm/s will be the lower bound for the violation response.

Detection resolution(DSM)

Verbal definition of KPI: The KPI will represent the smallest reliably detectable object for the sensor at given distance. Value gives information what kind of body part tracking could be done reliably if used as a safety sensor.

Way to measure KPI and data source: Three parts, representing common possible sizes (one small finger, two big fingers, palm) were tested at different heights relative to the table surface.

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Quantitate KPI: The table represents how far objects of different sizes should stand for consistent detection. The maximum detection resolution could be gathered after experiment, by acknowledging the borderline of losing the detection signal.

diameter (cm)	distance above table (cm)
1.21	44.5
3.07	18.4
6.3	2.88

Analysis and identification of areas of improvement for Use Case 1:
The violation was performed using deterministic robotic program, such that the pokes were executed in predefined points of the safety border. It can be the case that certain areas of the border would be less reliable for detection than the ones we've selected, so overall success rate would be lower. The test also doesn't take into account how different illumination conditions can affect the success rate. The improved test would randomize poke points around the border and run them under different illumination conditions. The limit on robot's movement speed doesn't allow us to test exact threshold at which the detection becomes unreliable. Replacing the robot with a different device would allow us to measure response time more accurately. The response time depends on multiple factors of the module, such as quality of the computational hardware used, projector's internal update rate, quality of the driver's used to message with the robot and the sensors. Decoupling those factors and showing how each of them could improve overall performance would make analysis more helpful to the user.

A.2 Use Case 2: Collaborative dis/assembly with augmented reality interaction

This use case utilizes AR technology in collaborative cell to provide functionalities such as safety monitoring, safety information and interactable user interface. Safety model that investigated in first use case is utilized to communicate with Microsoft HoloLens HMDs, next AR HMD augment the user instruction, and demonstrate safety borders in real time and actions required regarding facing safety measures.

Assembly Completion Time:

Verbal definition of KPI: The KPI will represent the required time from operator to finish successful engine assembly task.

Way to measure KPI and data source: User will start the assembly task by confirming it on AR HMD and follow all instructions for the assembly task. The completion time will be gathered by researcher with timer. Assembly completion time with AR system was compared to the assembly task without augmented user interface.

Quantitate KPI: The improvement in assembly task completion time in percentage is compared to non-collaborative system.

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Non-collaborative assembly	AR-based collaborative	Improvement
82.9 s	65.4	21-24%

Total Robot Idle Time:

Verbal definition of KPI: The KPI will represent the required time from robot to wait operator finishes the all tasks.

Way to measure KPI and data source: The motion of robot during the task is monitored in both AR and non-AR system and compared to the assembly task completion.

Quantitate KPI: The improvement in robot idle time in percentage is compared to non-collaborative system.

Non-collaborative assembly	AR-based collaborative	Improvement
27.6 s	12.0 s	57-64%

Analysis and identification of areas of improvement for Use Case 2:
The tests were performed on a small group of people from the university, whose subjective evaluation can differ from the people who may use this module in the industry. Performing tests with the users from the industry with a bigger sample size would make the estimation more accurate.

A.3 Use Case 3: Collaborative Robotics in Large Scale Assembly, Material Handling and Processing

An agile industrial robotization of a large-scale material handling, processing or prefabrication where robots and people will process components collaboratively is demonstrated. The working zone is monitored dynamically, and information is provided to both parties: the human worker and robot. Different multimodal human-computer interaction methods are evaluated. This ultimately leads to more agile robotized production, where humans and robots may work together in tasks such as large-scale assembly, material handling and processing. Main objective of this use case is to demonstrate the possibilities of large-scale industrial robotics in collaborative tasks. This use case demonstrates a novel combination of safety sensors and additional devices that make true human-robot collaboration possible, while still following safety regulations and standards. In addition, dynamic and flexible robot trajectory generations are demonstrated.

Production lead time: from start of manufacturing to final product:

Verbal definition of KPI: Production lead time from start to finish. Including set-up and re-configuration of robot.

Way to measure KPI and data source: Time to perform deburring process of enclosure from start to finish. Comparing conventional robot programming to reactive robot programming.

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Quantitate KPI:
Reactive solution:
Time consumed 10 - 60 minutes depending of the product complexity.
Conventional solution:
Time consumed 60 - 240 minutes depending of the product complexity.

Set-up time:

Verbal definition of KPI: Amount of time needed for setting up the machine including change of tools, fixtures, programs etc.

Way to measure KPI and data source: Time consumed to setup robot program to wash heavy equipment compared between conventional and reactive robot programming.

Quantitate KPI:
With the use case: 45 - 120 minutes depending of the product complexity for any product type.
Without the use case: 3 - 8 days depending of the product complexity for each product type.

Materials used by weight or volume:

Verbal definition of KPI: Amount of water required to wash a truck manually

Way to measure KPI and data source: Amount of water required to wash a truck using robots

Quantitate KPI:
Robotized solution:
Water consumed 100 - 200 liters (with efficient water circulation and cleaning system).
Manual Labour:
Water consumed 1000 - 2000 liters.

Labor safety:

Verbal definition of KPI: Percentage of human labor removed from hazardous environment

Way to measure KPI and data source: Percentage of persons required to wash a truck

Quantitate KPI:
Robotized solution:
100%, no person involvement in hazardous environment required
Manual Labour:
At least one person required.

Analysis and identification of areas of improvement for Use case 3:
Some improvements for the use case demonstration 3 could for example replacing ROS1 based modules with ROS2 to improve cybersecurity, and/or developing of more Open source solutions as alternatives of proprietary software.

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A.4 Use Case 4: Integrating digital context to the digital twin with AR/VR of the robotized production

The use case demonstrates the possibilities for utilizing digital context data into production of manufacturing companies, which provides an agile way for automating manufacturing processes. The use case involves utilizing BIM, VR/AR technology and a digital twin of a robotic production cell. These methods can be used for flexible monitoring, operational support, training, safety and maintenance purposes of the production cell. To showcase the use of digital context data in manufacturing. Integration of robot trajectory data into product design provides an agile way for automating manufacturing processes and speeds up the design-production timeline. Complete VR/AR environments can be built and used for flexible monitoring, support, training, safety and maintenance.

Training costs

Verbal definition of KPI: Saved costs in travelling for training

Way to measure KPI and data source: Take one experiment with Norway as the example, by using our remote-control solution, Narvik engineers can control Centria Robo3D Lab robots remotely. Measure the travelling time between Centria and UiT.

Quantitate KPI: By the estimating of Google map, the travel time from Centria in Ylivieska to UiT in Narvik and then back is 22 hours by car driving.

Direct economic value

Verbal definition of KPI: Reduce the training cost by replacing traditional teaching with virtual training

Way to measure KPI and data source: Compare the time required for safety training traditionally to virtual safety training

Quantitate KPI: Can be up to four times faster compared to traditional teaching. Based on company experiences (ADE oy)

Analysis and identification of areas of improvement for Use Case 4:
Some improvements such as implementing modules with open-source Game engine Godot and/or adding more augmented reality examples based on WebGL could be considered.

A.5 Use Case 5: Automated robotic welding

The industrial robot has an important role in the automation of the manufacturing industry and has considerably contributed to the improvement of profitability and working environments. However, there are still many tasks in the manufacturing industry that requires heavy work, such as welding and additive manufacturing based on welding. The objective of the demonstrator is to showcase how an industrial robot can be used for robotic welding and wire arc additive manufacturing (WAAM).

Set-up time reduction

Verbal definition of KPI: Percentage of time reduced compared with previous setup

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Way to measure KPI and data source: To test this KPI two tests are conducted, one for welding a line and a second test for welding a half circle. (Compare between Digital Twin solution and Teach Pendant programming)

Quantitate KPI: As described in the example of the introduction chapter
In the test the time from start of welding to the weld is done. From the test we got the following result:

	Robot welding (sec)	Manual welding (sec)	Percentage (%)
Welding line:	87	100	14.9
Welding circle:	155	173	11.6

Average reduced percentage = (14.9+11.6) / 2 = 13.25%

Re-configure time

Verbal definition of KPI: Compare the time it takes to re-program or re-setup a new product

Way to measure KPI and data source: We will measure the time it takes to program with the new interface compared to using the teach pendant. This will be done for the welding robot using the teach pendant and using the digital twin.

Quantitate KPI:

Programming method	Weld half circle (min)	Weld line (min)
Teach pendant programming	7.8	5.23
Digital twin programming	4.57	1.95

Reduced percentage = (Teach pendant programming - Digital twin programming)/Teach pendant programming
Half circle = (7.8-4.57)/7.8 = 41.4%
Line = (5.23-1.95)/5.23 = 62.7%
Average reduced percentage = (41.4 + 62.7)/2 = 52.05%

Cost-efficiency (reduce ownership cost)

Verbal definition of KPI: Reduce the cost of ownership (set-up, operational cost, maintenance, etc.)

Way to measure KPI and data source: Calculate the robotics engineer salary in hour, then multiply the reduced percentage (Set-up time reduced, re-configure time reduced percentage).

Quantitate KPI:

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Robotics Engineer average salary in Norway 2022 is 593000 NOK
http://www.salaryexplorer.com/salary-survey.php?loc=162&loctype=1&job=12657&jobtype=3
593000 NOK /12 Month /4 week/5 day/8 hour = 308 NOK /hour
Set-up cost reduced = 308 * 13.25% = 40.81 NOK/hour
Re-configure cost reduced = 308 * 52.05% = 160.31 NOK/hour

Analysis and identification of areas of improvement for Use Case 5:
The demonstrator exploits an industrial robotic arm to automate repetitive welding jobs that result in more consistent welds and fewer mistakes. Remote programming of the system (offline programming). This allows for verification of the welding program before running it on the physical robot and you can program the system without interrupting the current production which can save costs. Using robotic welding releases humans from the labour-intensive and hazardous work environment. The system can be used for additive manufacturing, to repair broken parts or 3D print parts. This can be a fast and cost-effective method to create or fix damaged parts.

A.6 Use Case 6 - Digitalization of a production environment

Factories of the future will face increasing demands for non-stop production, accompanied with high flexibility and safety requirements. This implies an important future market, for instant services dealing with support, error diagnostics and reconfiguration of industrial robot systems. These advances can be achieved by utilizing IoT in every stage of the production process in a factory. Based on the collected data, decisions can be made even from distant locations. This demonstrator illustrates how to create a digital copy of a production environment. It will also show how robots and other machines can be connected and controlled from the same industrial information server.

Accessibility

Verbal definition of KPI: Level of open source-based software

Way to measure KPI and data source: Calculate the amount of open-source software we have used compared to the one that are not open source

Quantitate KPI:
Open-source software: Python, OPCUA, PyCharm, ROS, MoveIt, Node-red, KUKA RSI, KUKAVARPROXY, Ubuntu

Commercial software: Visual Components, Visual Components Experience, Windows 10, TeamViewer, Azure Cloud, MiR software

KPI: Open: 9 Not-open:6

Cost-efficiency (reduce travel time)

Verbal definition of KPI: Reduce the time of operators traveling

Way to measure KPI and data source: Take one experiment with Finland as the example, by using our remote-control solution, Centria engineers can control the Nachi robot remotely. Measure the travelling time between Centria and UiT.

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Quantitate KPI: By the estimating of Google map, the travel time from Centria in Kokkola to UiT in Narvik and then back is 22 hours by car driving.

Cost-efficiency (reduce operator number)

Verbal definition of KPI: Reduce the number of operators, one operator can control multiple robots

Way to measure KPI and data source: The traditional way of programming industrial robots needs one operator to hold the teach pendant of the robot. By using usecase 6, one operator can control KUKA robot, Nachi robot, Scara robot at same time.

Quantitate KPI: The number of operators reduced from 3 to 1

Cost-efficiency (automation replace manual)

Verbal definition of KPI: Reduce the cost by using robot instead of manual work

Way to measure KPI and data source: Calculate the human salary and the robot cost, then compare it.

Quantitate KPI:
Norway average month salary 48750 NOK
48750 NOK /4 week/5 day/8 hour = 299 NOK / hour
Industrial robot system investment cost around 300000 NOK, expected working for 10 years.
300000 NOK/10 year / 365 day / 24 hour = 3.42 NOK / hour

KPI: 299 vs. 3.42

Analysis and identification of areas of improvement for Use Case 6
The main benefits of the demonstrator revolve around increased flexibility by digitalizing a production environment and connecting robots and other machines together. Data from a production system can give an enhanced insight into the performance of the system for improved visualization. It creates a unified method for robot programming which simplifies and standardizes the procedure of robot programming. Which again creates a friendly and simple environment for training of employees. The system is made to be flexible and scalable, where robot arms, mobile robots and other machines can be added or removed to the IoT system without compromising the current system. The use case creates an agile method for connecting robots and other machines together through a standardized industrial information server (OPC UA standard).

A.7 Use Case 7 - Robot workcell reconfiguration

The aim is to provide the manufacturing SMEs and also larger manufacturing companies effective software and hardware components to quickly reconfigure manufacturing workcells in order to switch from one production process to another. Innovative reconfigurable hardware elements with passive (non-actuated) degrees of freedom enable partial autonomous (robot-aided) reconfiguration of robot workcells. Passive fixtures, based on Stewart platforms, are used to adapt the fixture points based on the current product. ROS-based software provides necessary modularity to exchange the workcell's software and hardware components, as required when switching from one production tasks to another. Software tools include,

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among other, automatic computation of optimal postures of fixtures and workpieces, and robot control for robot-aided reconfiguration of the available passive hardware elements.

Times of reconfiguration (HW & SW):

Verbal definition of KPI: The time to reconfigure the full cell can include manual, automatic, and robot-aided reconfiguration of hardware components. In addition, software must enable adaptation to change to various products. This KPI was determined based on 4 implemented cases from various sectors calling for different levels of needed reconfiguration.

Way to measure KPI and data source: The time was determined as an average value over 4 different cases. As this KPI is highly depended on similarity and familiarity of the products, it is given in four values.

Quantitate KPI:
- Known product to another known product within the same family: ~2 min
- Known product to another unknown product within the same family: 1 day
- Known product to another known product from another family: ~5 min
- Known product to another unknown product from another family: 15 days

Time of robot-aided reconfiguration

Verbal definition of KPI: Robot-aided reconfiguration time is defined as the time needed to change the process from one product to another, when all the reconfiguration can be done with the robot and no manual intervention is needed. While manually reconfigurable elements can be included in the cell, this KPI focuses only on robot-aided reconfiguration of fixtures. The time needed to reconfigure the workcell depends highly on the products and needed reconfigurable elements.

Way to measure KPI and data source: A specific case from the automotive industry was used to quantify this KPI, where the cell reconfigured between two products from the same family. In order to further detail the KPI, not just full reconfiguration is looked at, but also sub-reconfigurations.

Quantitate KPI:
- Full reconfiguration 4'4"
  The time needed to fully reconfigure the cell, including the repositioning of the three fixtures and exchanging three holding pins.
- Fixture layout reconfiguration 42"
  The time needed to reconfigure all three needed fixtures.
- Single fixture reconfiguration 12"
  The time needed for a single fixture reconfiguration.

Computational time for optimal layout

Verbal definition of KPI: As determining optimal layout of passive fixtures is near to impossible by hand, optimization processes are used to determine it. This KPI looks at computational time needed for layout computation based on desired inputs (product CAD models, cell footprint, workspace limitation, etc.).

Way to measure KPI and data source: We performed optimization for layouts with $M = 2, \ldots, 6$ workpieces and $N = 3, \ldots, 6$ hexapods (or fixture points), thus altogether 20 different layouts. The

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arrangement of fixture points on each modular workpiece was randomly selected. The optimization procedure was executed on a desktop computer with the 4th generation Intel Corei7-4790K CPU having 4 cores running at 4.00 GHz base frequency and 16 GB of RAM.

Quantitate KPI: The bar graph shown on the left illustrates the computation time needed to solve each optimization problem, whereas the bar graph on the right presents the time needed for one evaluation of the criterion function and constraints.

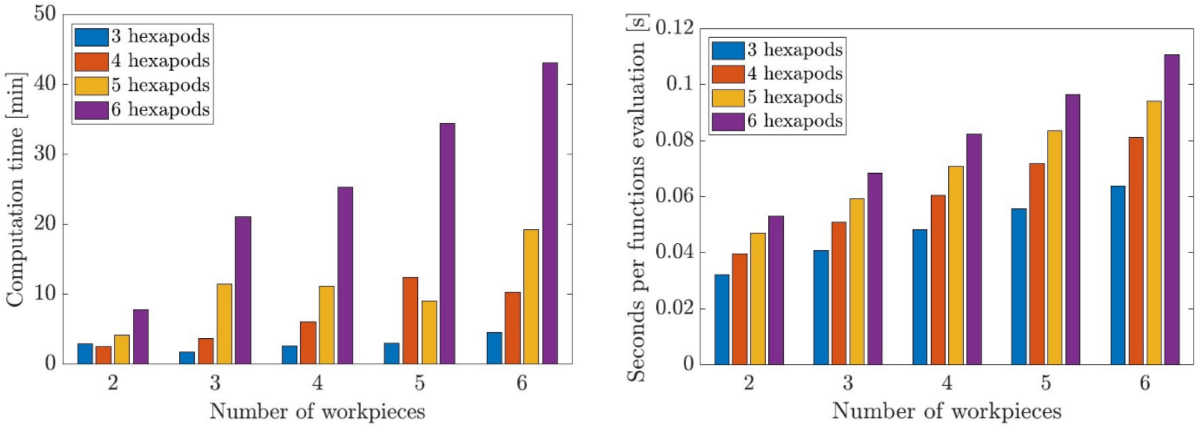

Figure 1 Computation time needed to solve each optimization problem

Analysis and identification of areas of improvement for Use Case 7
The optimization procedure was executed on a desktop computer. If optimization ran often, a dedicated machine would improve calculation times. Optimization or transfer of code would further improve computation times. Changing of pins is time consuming. If possible, we could improve pins/workpieces/production process to avoid or minimize the need. Robot movements are not optimal during evaluation of fixture reconfiguration times. Optimization of trajectories could be considered for reconfiguration and for ensuring robot's full speed.

A.8 Use Case 8 - Efficient programming of robot tasks by human demonstration

End-users often cannot program their robots without the help of system integrators, as traditional systems for programming of industrial robots are still quite complex and rely on users possessing extensive knowledge about advanced robotics concepts. This in turn prolongs the required programming time and increases the price of robot applications. Use Case 8 address these challenges by providing a software and hardware framework that include both front-end and back-end solutions to integrate programming by demonstration paradigm based on kinesthetic teaching into an effective system for programming of robot tasks, e.g. automated robot assembly.

Effect of virtual mechanism for hard to transfer tasks

Verbal definition of KPI: A force-based task of grinding/polishing is considered a representative hard to transfer industrial task. This type of a tasks can be transferred via learning by demonstrations using various sensors, e.g. digitizer with force/torques sensors. To facilitate execution of a learned grinding/polishing task on an industrial robot, an approach based on virtual mechanisms has been implemented. It takes advantage of redundancies stemming from the task and tool shape. The effect of virtual mechanism was

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evaluated by looking at peak joint velocities of the robot and successfulness of task execution at different points in the robot's workspace.

Way to measure KPI and data source: The grinding machine, i.e. the desired point of task execution, was moved to several different locations in the robot's workspace. The same learned grinding task was executed at each of the locations. The orientation of the grinding machine and its height was not changed. In addition peak joint velocities were recorded.

Quantitate KPI: The results, seen in figures below, show the increase of the robot's workspace, where the task can be performed and a significant drop in peak joint velocities.

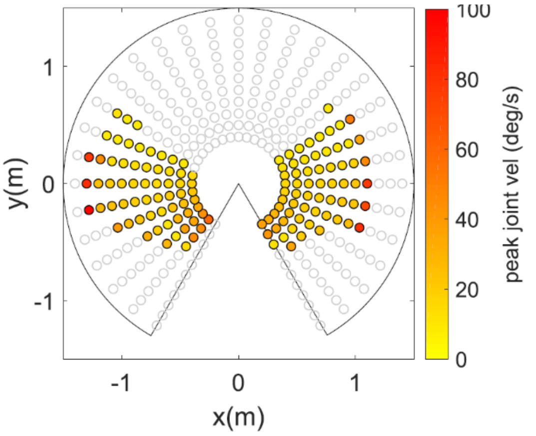

Figure 2 Without virtual mechanisms

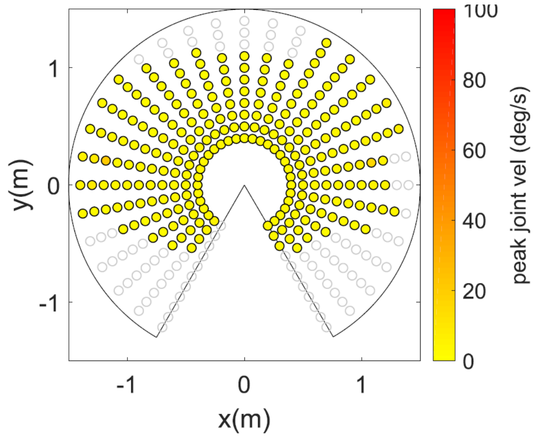

Figure 3 With virtual mechanisms

Quality and efficiency of incremental policy refinement by human demonstration

Verbal definition of KPI: To shorten the time necessary to deploy robot tasks, we need appropriate tools to enable efficient reuse of existing robot control policies. Incremental Learning from Demonstration (iLfD) and reversible Dynamic Movement Primitives (DMP) provide a framework for efficient policy demonstration and adaptation. The quality and efficiency of the approach was evaluated with a comprehensive user study.

Way to measure KPI and data source: Different aspects were looked at in the user study for the three learning methods: 1) classical kinesthetic guidance (KG), i.e. manual guidance, 2) incremental policy refinement using batch regression (BR), and 3) incremental policy refinement using recursive regression (RR). During the experiment, the participants stood next to a small table with a shoe model mounted and were instructed to move the robot in such a way that the tip of the stick moves along the edge of the shoe sole from a start to the goal point which were both marked visually on the shoe. Task was performed using all three learning methods. Nineteen healthy subjects participated in the study (13 male, 6 female, age: 34.63 ± 14.59 years).

Quantitate KPI: The plots in the below figure shows the means and standard errors (SEM) for different aspects for the three learning methods. We can observe incremental learning reduces error, shortens learning time and improves the user experience.

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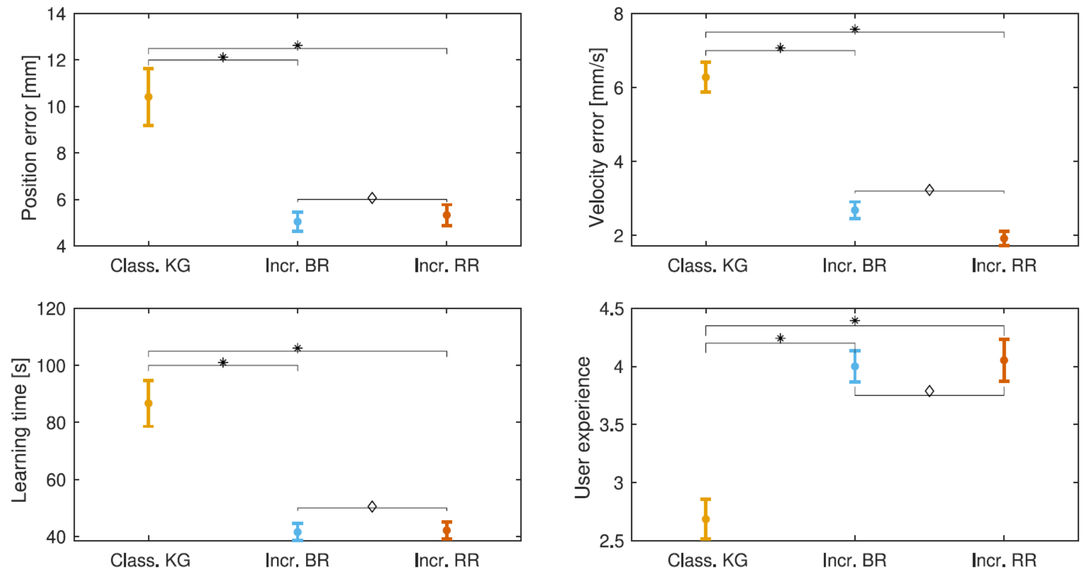

Figure 4 the means and standard errors (SEM) for different aspects for the three learning methods

Analysis and identification of areas of improvement for Use Case 8

There are also some exceptions where our approach of incremental learning cannot be directly applied, e. g. when we need to modify the trajectory in the tangential direction. Changing the depth of peg insertion is such a case. Extensions that allow coping with such issues remain for our future work. With hard to transfer tasks, some finishing operations in industrial environments require the acquisition of several different finishing policies, which must be automatically combined and sequenced to treat different workpieces successfully.

A.9 Use Case 9 – Dynamic task planning & work reorganisation platform

This use case focuses on the planning of tasks' allocation among the available resources in HRC processes. Task allocation in synchronous HRC environment including several resources is a time-consuming process which currently takes place manually by the teams of production's managers. In order to overcome the time-consuming process of designing a new human-robot task allocation plan and reduce the time and size of the design team needed for applying a change to an existing line, this module suggests a multi – level decision making framework targeting on the dynamic work balancing among the human operators and robot resources using a task planner algorithm. This will allow the evaluation of a huge number of alternative solutions in a short time frame, even in cases where reconfiguration of the production line is needed. A suitable Task planning regarding the available human and robot resources will be generated automatically. An intelligent decision-making framework for task allocation to the available resources in the production line, motion planning of robot operations and criteria estimation will be implemented. The 3D graphical representation, simulation and embedded motion planning for both humans and robots will be possible.

Re-configure time

Verbal definition of KPI: The AI task planner module is reconfigurable in terms of easy changes on search parameters and weight values of evaluation metrics, through its UI.

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Way to measure KPI and data source: Measure the average time the task planner needs to generate and evaluate new alternative task plans based on new search parameters and weight values of the evaluation criteria, starting from a clean stop.

Quantitate KPI: This KPI has been measured through testing. During the execution of a planning process, the user stopped the AI task planner through the developed UI and the time duration calculated from this time frame until the end of the planning parameters' update through the corresponding UI tab and planner's execution trigger. The average duration of the planner's reconfiguration was 3 minutes.

Cycle time

Verbal definition of KPI: The developed AI Task Planner module is able to generate and evaluate different task plans alternatives and provide to the production manager the top three alternatives in a specific amount of time. The cycle time depends on the search algorithm parameters but for the selected use case it has been observed that the following values give good results [DH, MNA, SR] = [2, 2, 2].

Way to measure KPI and data source: Measure the average time the task planner needs to generate and evaluate alternative task plans.

Quantitate KPI: This KPI has been measured through testing. The average duration of the planner's cycle time was 2.5 hours.

Set-up time

Verbal definition of KPI: The time needed to model the resources and tasks but also setup the simulation environment with intermediate knowledge on ROS

Way to measure KPI and data source: Measure the average time required by a user with intermediate knowledge on ROS to configure the planner, creating models for the resources and tasks but also setup the simulation environment.

Quantitate KPI: It has been measured that 3 weeks are needed to setup the AI task planner in terms of tasks and resources modelling but also the required simulation environment.

Labor Safety

Verbal definition of KPI: The total weight of the payload that the operator could handle during a generated task plan execution can be adjusted through the respective parameters through the task planner's UI.

Way to measure KPI and data source: Measure the reduction of the total weight that the operator handles during the execution of each generated task plan. This information is provided by the AI-based Task Planner, using tasks' and resources' models. This number is calculated using the following equation:
*(Operator handling weight during generated task plans execution / Initial operator handling weight) * 100%*

Quantitate KPI: 50% (Operator handles parts of maximum weight 1 kg).

Reduction of waiting time for human operators, parts and products

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Verbal definition of KPI: Reduction of the idle operator time waiting for parts and products to become available or being processed.

Way to measure KPI and data source: Measure the reduction of the idle operator time during the execution of each generated task plan. This information is provided by the AI-based Task Planner thanks to tasks and resources' modelling. This number is calculated using the following equation:
*(Operator idle time during generated task plans execution / Initial operator idle time) * 100%*

Quantitate KPI: 40%.

Analysis and identification of areas of improvement for Use Case 9
Design and implementation a more user-friendly interface for the task planner should be created. This could incldude parameters providing more details about the tasks modelling to the production manager. Design and implementation of a generic ROS interfaces for the AI task planner should be realised. This would allow better the system to communicate with more simulation tools for generated task plans simulated execution during the validation and evaluation phase.

A.10 Use Case 10 – AR based operator support in HRC / HRI framework for operator support in HRC operations

In currently established production systems, the operator support is based mainly on paperwork (to provide assembly instructions) or dedicated monitors on PCs located in each workstation. Thus, the operator is not able to have access to this information while working in the station. At the same time, the paperwork-based instructions need to be constantly updated when new products or new variations are introduced. Additionally, the paper-based information sharing approach could not be used in other cases, such as informing the operators for potential hazards or provide information on the status of the production. This use-case demonstration aims at enhancing operator support by providing instructions and production-related information through an AR application. Furthermore, the implemented AR app also targets at increasing operator's "safety feeling" and acceptance when working close to large industrial robots by visualizing data coming from a robot's controller and by displaying visual alerts to increase their awareness for a potentially hazardous situation (Figure 1).

To this direction, the developed AR Application provides to the human operators:

- Assembly instructions
- Robot behaviour information for increasing safety awareness
- Safe working volumes
- Production status information

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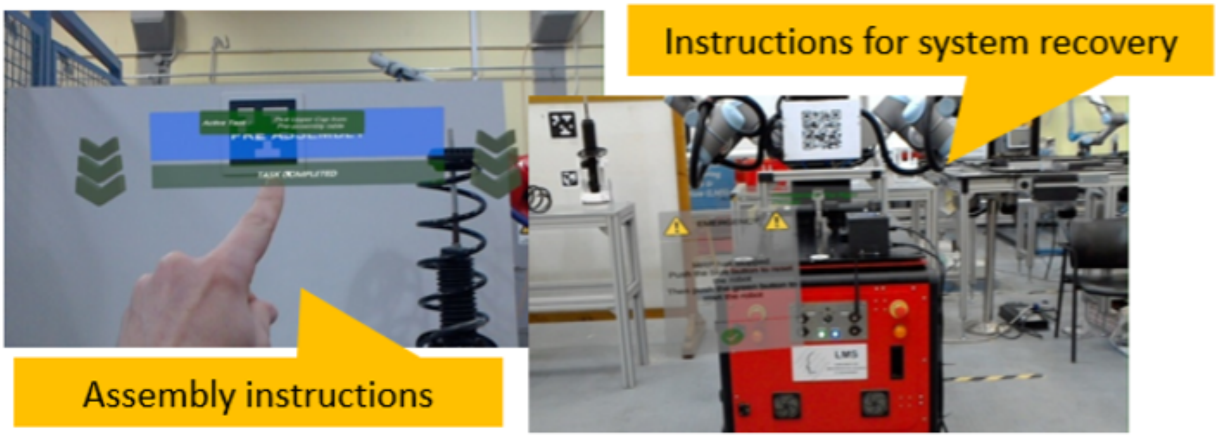

Figure 5 AR Application functionalities

Set-up time

Verbal definition of KPI: The time needed to setup the AR application.

Way to measure KPI and data source: Measure average time to deploy the AR application.

Quantitate KPI: 10 minutes.

Training time

Verbal definition of KPI: The time related to the training of the operator to use the AR application.

Way to measure KPI and data source: Consider average time needed to train an operator to use the AR application.

Quantitate KPI: 1 hour.

Accessibility

Verbal definition of KPI: The level of open source-based software used to develop the components of the Use Case.

Way to measure KPI and data source: Consider whether the software tools used during the Use Case implementation are open source or require a purchased license.

Quantitate KPI: Three main software components are used for the Use Case implementation:

- Safety sensors configuration software → License purchase is required
- Unity3D (and the Vuforia library) for building the AR application → open-source
- ROS framework → open-source

Therefore, 2/3 of the required software components are based on open-source libraries.

Training Costs

Verbal definition of KPI: The cost related to the training of the operator to use the AR application.

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Way to measure KPI and data source: Consider average 1 hour needed to train a small group of operators to use the AR application and 80 euros the average hourly rate.

Quantitate KPI: Measurement: Training cost = (training cost) * training time, where training cost = cost per hour of training
Training cost = 80 euros per group

Analysis and identification of areas of improvement for Use Case 10

The possible ways forward would be to enhance robot behaviour information provided by projecting robot's future way of movement to increase operator awareness. Secondly to enhance AR application functionalities to provide the operators ability to reprogram the robot through the application. And possibly also to include voice commands support to the application to interact with the robot during execution. And finally, to simplify the process of creating assembly instructions through user-friendly GUIs.

A.11 Use Case 11 - Robotized serving of automated warehouse

The demonstrator was created as a fully functional, scaled-down, table-top model of an automated warehouse served by an omnidirectional mobile robot. The specific goal was to demonstrate the feasibility of using omnidirectional mobile robots in intralogistics. The demonstrator is based on a mobile robot equipped with three Omni wheels (Kiwi-drive). The automated warehouse in the demonstration is a pen-vending machine operated by a microcontroller. The vending machine has three slots for holding three different coloured pens and serving one pen at a time. The robot recognises the task by a label-coded card shown to its camera using optical character recognition (OCR). The potential users are SMEs dealing with smart assembly involving mobile robots. The demonstration incorporates existing AGV technologies widely used in intralogistics (optical line following) and emerging technologies (visual servoing). Possible benefits include applications with mobile robots, optical character recognition, target detection, and controlled manoeuvring, path tracking without compromising safety. The owner of the demonstrator is the Budapest University of Technology and Economics (BME).

Cycle time

Verbal definition of KPI: The time it takes to perform one cycle of operation from start to finish. The operation is the full order-delivery cycle (see figure below). It includes the waiting steps that are part of the process.

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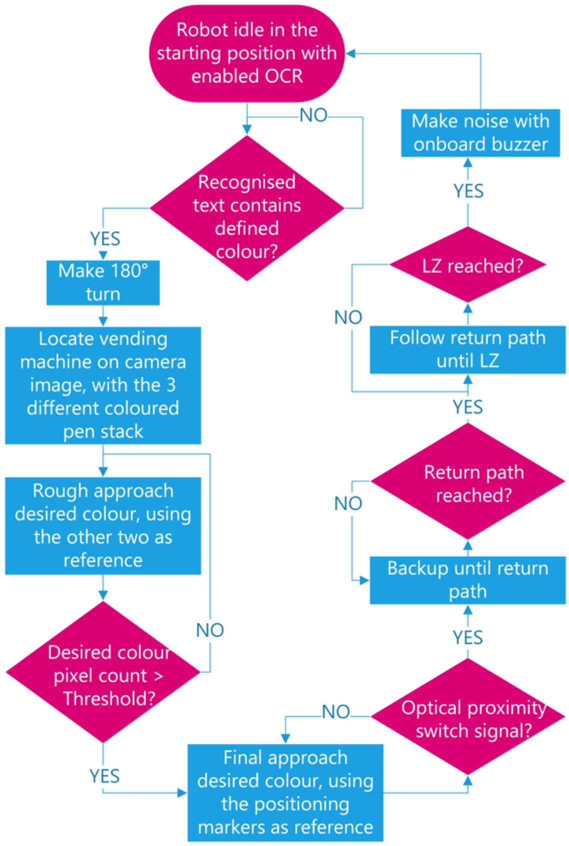

Figure 6 The full order-delivery cycle

Way to measure KPI and data source: The KPI can be measured directly in the robot control software by subtracting the current time when a label-coded card is recognised, and the robot arrives at the starting position. The result is given in Seconds per Part.

Quantitate KPI: Results of four consecutive order-delivery cycles:

Cycle number	Cycle time (s/part)
1	59
2	57
3	54
4	59
Average	**57.25**

Throughput rate

Verbal definition of KPI: The Throughput rate is the number of cycles of operation done from start to finish in a given period.

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Way to measure KPI and data source: The KPI can be measured directly in the robot control software by calculating the reciprocal of the Cycle time. The result is given in Parts per Minute.

Quantitate KPI:
Results of four consecutive order-delivery cycles:

Cycle number	Throughput rate (parts/min)
1	1.02
2	1.05
3	1.11
4	1.02
Average	**1.05**

Energy Consumption

Verbal definition of KPI: Energy Consumption is the amount of used electrical energy in one cycle of operation from start to finish.

Way to measure KPI and data source: The KPI can be measured directly in the robot control software by calculating the weighted sum of the products of the electrical current consumption with the battery voltage in each refresh cycle between the mobile robot and the control PC. The weight is the periodicity of the refresh cycle: 10 ms. The result is given in watt hours (Wh).

Quantitate KPI: Results of four consecutive order-delivery cycles:

Cycle number	Energy Consumption (Wh)
1	1.27
2	1.23
3	1.16
4	1.27
Average	**1.23**

Analysis and identification of areas of improvement for Use Case 11
Although the advantages of using an automated warehouse are apparent through the demo, the benefits are not quantifiable. Accordingly, the end customer benefits are positive. The economic impact cannot be applied directly to the demonstrator. Omnidirectional drives, especially Kiwi-drive systems, are rarely used in intralogistics due to their complexity. Baseline values cannot be found because every solution is different. The KPIs could deviate by orders of magnitude. The KPIs are based on the goods transported, the effective length of the path the robots cover, the characteristic travelling speeds, etc.

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Generally, the selected KPIs can be improved in the following ways:

- Cycle time and Throughput rate can be improved by increasing the characteristic travelling speeds or by shortening the path,
- Energy Consumption can be improved by decreasing the characteristic travelling speeds or by lowering the overall mass of the mobile robot, including the transported goods.

A.12 Use Case 12 - User-friendly human-robot collaborative tasks programming

There is a shift from mass production to mass customization which implies a constant need for robot programming/reprogramming. This process requires time and expertise which is therefore very costly. The goal of this demonstrator is to intuitively program and reprogram a collaborative robot by means of a user-friendly user interface to lower the programming time but also the required expertise. To validate the benefits of the user-friendly module in manufacturing industries, a relevant industrial use-case is selected which is the assembly of an air compressor from Atlas Copco composed of various elements. The assembly is performed from a kitting tray. This assembly consists of various jobs with varying complexity. The most complex steps are the peg-in-hole of the screw rotors inside the compressor housing.

The main goal of the experimental validation is to perform the air-compressor assembly using the intuitive programming framework. Initially, the operator receives a basic overview of the skill-based framework and how to interact with it. The operator starts his experimentation with the main page of the web interface. The experiment consists of programming the assembly sequence by an appropriate sequence of skills and parametrization of the device primitives. The operator will be free to select the different skills of interest to correctly perform the complete assembly. The second experiment consisted of modifying the existing task for a product variant. In comparison with the first assembly, the kitting tray is moved and fixed to a different location. Consequently, all the kinematic parameters needs to be adjusted for this second experiment. In addition, the housing of the compressor is made with a cast iron process. The main consequence of this lays in the different force parameters that also differs from the first assembly and requires significant changes in the device primitive parameters. At the start of the experiment, the operator will re-use the previously taught application. To adapt the skills and device primitives, positions need to be adapted to match the new locations.

Programming time

Verbal definition of KPI: Time to program an assembly from the user interface (with robot and gripper previously configured).

Way to measure KPI and data source:
Simple assembly: time to intuitively perform an assembly with a minimum of 4 pick and place operations.
Complex assembly: time to intuitively perform an assembly with a minimum of 4 pick and force-based insertion operations.

Novices are persons with no knowledge in robotics, experts have experience in robotics.
The measure of the KPI is performed by recording the time it takes to perform the programming of a simple/complex assembly.

Quantitate KPI:
Simple assembly: 30min

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Complex assembly: 56min (novice), 46 min (expert)

Reprogramming time

Verbal definition of KPI: Time to reprogram an assembly from the user interface. The intuitive reprogramming consists in modifying an existing program that was intuitively taught.

Way to measure KPI and data source:
Simple assembly: time to intuitively perform an assembly with a minimum of 4 pick and place operations.
Complex assembly: time to intuitively perform an assembly with a minimum of 4 pick and force-based insertion operations.

Novices are persons with no knowledge in robotics, experts have experience in robotics.
The measure of the KPI is performed by recording the time it takes to perform the reprogramming of a simple/complex assembly.

Quantitate KPI:
Simple assembly: 15min
Complex assembly: 32min (novice), 23 min (expert)

Skill programming time

Verbal definition of KPI: Time to program a simple skill (e.g. Pick) or a complex skill (e.g. Forced-based insertion).

Way to measure KPI and data source: The measure of the KPI is performed by recording the time it takes to perform the programming of a simple/complex skill.

Quantitate KPI:
Simple skill< 5 min
Complex skill < 10 min

Teach by demonstration time

Verbal definition of KPI: Time to teach a simple pose by guiding the robotic arm to a specific location.

Way to measure KPI and data source: The measure of the KPI is performed by recording the time it takes to perform the programming of a point by guiding the robotic arm to a specific location.

Quantitate KPI: < 30s

Teach trajectory by demonstration time

Verbal definition of KPI: Time to teach a trajectory (set of joint positions) by guiding the robotic arm through a set of specific locations.

Way to measure KPI and data source: The measure of the KPI is performed by recording the time it takes to perform the programming of the multiple points by guiding the robotic arm.

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Quantitate KPI: < 1min

Launch full application time

Verbal definition of KPI: Time to launch the application from a compiled code with robotic and gripper devices being properly configured.

Way to measure KPI and data source: The measure of the KPI is performed by recording the time it takes to launch the application through the command line terminal in Ubuntu and properly launch the robotics application on the teach pendant.

Quantitate KPI: < 5 min

Easiness in application

Verbal definition of KPI: Time to re-program an application from an idea to operation.

Way to measure KPI and data source: The measure of the KPI is performed by recording the time it takes to test several ideas of robot sequence of actions and skills (with parameter tunning).

Quantitate KPI: 1-2 hours (this measure is heavily dependent on the full application)

Analysis and identification of areas of improvement for Use Case 12
The improvement for the use case could include e.g. extending the device library of Easy Programming Module to cover a larger variety of robot and gripper: UR, MiR, KUKA KMR, Franka Emika Panda, OnRobot, Schunk, etc. and showing that different brands of robot and grippers can achieve the assembly by interacting with the same developed interface for the offline programming. The skill library could be extended to include the available device primitives can be extended to allow a larger variety of operations. And finally the user interface could be improved to be more intuitive and therefore save programming time (e.g. add sliders, improve navigation in the interface, etc.).

A.13 Use Case 13 - Deployment of mobile robots in collaborative work cell for assembly of product variants

The aim of this demonstrator is show the capabilities of mobile manipulators in work places shared by humans. Mobile collaborative robots allow to deploy robotics in manufacturing operations with unlimited reach. Their on-board and external sensing systems allow to realize autonomous and agile manufacturing that can cope with variability. Achieving higher reconfigurability and flexibility with mobile manipulators require intuitive and quick reprogramming. KMR iiwa is a combination of LBR iiwa robot and an omnidirectional mobile platform KMP 200 omniMove with high degree of flexibility and mobility programmed on Sunrise.OS. Sunrise.OS uses classical programming methods requiring an expert with profound background in JAVA. In context of flexible assembly tasks, the application programmed can neither be scaled up nor reused and reprogramming is required from scratch with new setting. Hence, there is a need for an intuitive and quick programming/reprogramming interface for KMR iiwa which can be easily used in conjunction with skill-based programming frameworks. Developed toolbox works on top of the KUKA Navigation Solution utilizing the autonomous functionalities of the KMR iiwa. Mobile kitting application for compressor parts was developed using the proposed toolbox. Developed toolbox

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allowed reproducing the application quickly and flexibly even with different frameworks & in different setting with decreased time and effort. Another module that has been developed and is being used in the validation cases is indoor positioning toolbox based on Ultra-Wideband (UWB) radio technology. The goal of this module is to enable localization of mobile objects in GPS-denied environment.

Programming time

Verbal definition of KPI: Time to program a mobile manipulation application for kitting of parts.

Way to measure KPI and data source:
Simple application: Go from Location A to B -> Go from Location B to C
Complex application: Go from Location A to B -> Perform task X -> Go from Location B to C
The measure of the KPI is performed by recording the time it takes to perform the programming of a simple/complex application.

Quantitate KPI:
Simple application: < 15 min
Complex application: < 30 min

Reprogramming time

Verbal definition of KPI: Time to reprogram a mobile manipulation application for kitting of parts.

Way to measure KPI and data source:
Simple application: Go from Location A to C -> Go from Location C to B
Complex application: Go from Location A to B -> Go from Location B to C -> Perform task Y
The measure of the KPI is performed by recording the time it takes to perform the reprogramming of a simple/complex application.

Quantitate KPI:
Simple application: < 5 min
Complex application: < 5 min

Continuous tracking of robot's pose

Verbal definition of KPI: Possibility to continuously monitor mobile robot's pose (position and orientation).

Way to measure KPI and data source:
Simple application: Go from Location A to B -> Go from Location B to C
Complex application: Go from Location A to B -> Perform task X -> Go from Location B to C

The measure of the KPI is performed by recording the mobile robot's position and orientation while performing of a simple/complex application.

Quantitate KPI: Robot's pose availability: > 99% of the time within the coverage area

Accuracy

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Verbal definition of KPI: Accuracy of estimated pose (position and orientation) of mobile robots.

Way to measure KPI and data source:
Simple application: Go from Location A to B -> Go from Location B to C
Complex application: Go from Location A to B -> Perform task X -> Go from Location B to C

The measure of the KPI is performed by recording the mobile robot's position and orientation while performing of a simple/complex application and compare the results with a ground truth system. The ground truth that we used is Qualisys System, which is position tracking system based on infra red signal, with accuracy of +/- 2mm. The robot's pose error can be reported statistically using cumulative distribution function (CDF)

Quantitate KPI: 2D Position error: < 20 cm, 90% of the time, 2D Orientation error: < 20 degrees, 90% of the time

Update rate

Verbal definition of KPI: Update rate (refresh rate) of estimated pose (position and orientation) of mobile robots.

Way to measure KPI and data source:
Simple application: Go from Location A to B -> Go from Location B to C
Complex application: Go from Location A to B -> Perform task X -> Go from Location B to C

The measure of the KPI is performed by recording the mobile robot's position and orientation while performing of a simple/complex application and calculate the refresh period for each new pose estimates.

Quantitate KPI: Robot's pose update rate: > 5 Hz, 90% of the time

Set-up time

Verbal definition of KPI: Amount of time needed for setting up the use-case experiment conditions (including change of tools, fixtures, programs etc)

Way to measure KPI and data source: The measure of the KPI is performed by recording the time it takes to setup the use-case for programming of a simple/complex application.

Quantitate KPI: < 4hr (includes mapping and setting up locations, graphs, etc.)

Analysis and identification of areas of improvement for Use Case 13
The improvements could be for extending the device library of motion toolbox to cover a larger variety of Mobile robots: MiR, UR, other autonomous mobile manipulators, etc. and showing that different brands can achieve the assembly by interacting with the same developed interface. The motion class as well as the available device primitives can be extended to allow a larger variety of operations. The user interface could be improved to be more intuitive and therefore save programming time (e.g. add sliders, improve navigation in the interface, etc.). Some improvements could be for e.g. to add more details for reconfigurability into the GUI interface, add non-blocking execution of skills, extend the KMR toolbox to include parameterized

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manipulator skills/combination of easy programming framework for manipulator with mobile robot skills, and finally extend the UWB module to include autocalibration of anchors positions.

A.14 Use Case 14 - Virtualization of a robot cell with a real controller

This use case enables the control of simulated manufacturing hardware using a real controller. The simulated hardware is represented in a real-time 3D-environment which can be used for demonstrating actual system functionality, training employees, virtual commissioning and testing production operations for new parts. These activities can be done before the system even exists or after commissioning, when they can be done without disturbing the ongoing production. This way changes can be made and tested without losing valuable production time. It also means that the layout design can be iterated multiple times before committing to the final one. Since the control software used is identical to the real-world control software all master data created with the virtual system can be transferred to the real one which speeds up the ramp-up phase of the system. The key element with this module is that the control software thinks that it is controlling a physical system. This way the behaviour of the system stays identical between the physical and virtual counterparts. It also means that all of the skills learned with one version will directly translate to the other one. This use case simulates production on a flow/process level and does not simulate the internal processes of machine tools or other similar devices in the system. The goal of the demonstrator is to reduce lost production time during training and re-configuration by moving the work to a virtual counterpart/environment.

Re-configure time

Verbal definition of KPI: The amount of time can be saved from the re-configuration/introduction of a new part into the system.

Way to measure KPI and data source: Time saved (%) when configuring the cell using a virtual counterpart instead of the physical cell. This can be measured in two datasets in which the first is done with the virtual cell and the latter is done with a physical cell. The time saved is the difference in times between these two.

Quantitate KPI: ~20-25% of re-configure time can be saved.

Training time

Verbal definition of KPI: The percentage of allocated training time that can be carried out virtually.

Way to measure KPI and data source: Production time saved when employees are trained with a virtual system instead of a physical one. This is measured as the amount of training time that can be carried out virtually.

Quantitate KPI: ~80% of allocated training time can be carried out virtually.

Technology swap feasibility:

Verbal definition of KPI: The percentage of system components (HW/SW) that can be swapped for similar ones without major changes to other components during the lifecycle of the demonstrator.

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Way to measure KPI and data source: Estimate of the amount of components (%) that are not specific for the operation of the system. E.g. the simulation model, hardware, etc.

Quantitate KPI:
What can be swapped: Simulation workstation and peripherals, Simulation software, The cell controller (hardware that MMS runs on)

What cannot be swapped: Fastems specific software (MMS), Operating system (Windows)

In general ~75% of system components (HW/SW) can be swapped for similar ones without major changes to other components.

Labour safety

Verbal definition of KPI: Percentage of allocated training time can be carried out virtually.

Way to measure KPI and data source: Practically this is the same amount of time (%) that is spent training or creating part master data. Depends highly on the customer and use cases. Measured as the percentage of time that operators can do work outside of the factory floor or other hazardous environments with the virtual system.

Quantitate KPI: ~80% of allocated training time can be carried out virtually.

Analysis and identification of areas of improvement for Use Case 14
The use case leans heavily on the principle of shifting on-line tasks, like training and new part introduction and testing, to virtual model of a robotic cell. The majority of the saved on-line time can thus be used for producing parts on the production system, instead of carrying out the training tasks with it. This is at the heart of the monetary benefit of the use case. To aid in evaluation of the feasibility of the investment to such a system, a more detailed description of the tasks that can be transferred to the virtual model would help in estimating whether the investment to such a system makes sense. This way the KPI's of the of the system could also be formulated in more detail to also further elaborate the return-on-investment analysis. The use case could be better integrated into the MMS UI so that no additional software is needed to run the use case. This would make the use case more cost-effective and user friendly. This would also reduce the hardware requirements as a dedicated PC would no longer be needed. The use case could be improved to provide more details about the simulated manufacturing process. This means that various KPIs could be integrated into the simulated environment and then these metrics would be displayed to the user.

A.15 Use Case 15 - Industrial IoT Robustness Simulation

The Industrial IoT Robustness Simulation provides an extensible and highly configurable discrete event simulator. The implementation of different simulation models is realizing a simulation for wireless sensor networks in a 3D environment. The two modules that are emphasized by the TRINITY project are "Network Device Positioning" and "Cyber-security Fallback Simulation". Both new software artifacts are extending the core functionality of a software project called NordicSim - Network Device Simulation. The NordicSim project is an open-source library and to simulate wireless sensor networks in order to support the integration process of such IIoT networks in the factory domain. Figure 1 shows the virtual IIoT network applied to the CAD model of the Research Factory at Fraunhofer IWU. The blue anchor nodes are establishing an indoor real time localization system (RTLS) and the green nodes are mobile and battery powered devices

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that are localized by the infrastructure. The scenario is also implemented as real RTLS inside the real factory hall. This scenario will be used as example for the upcoming KPI descriptions.

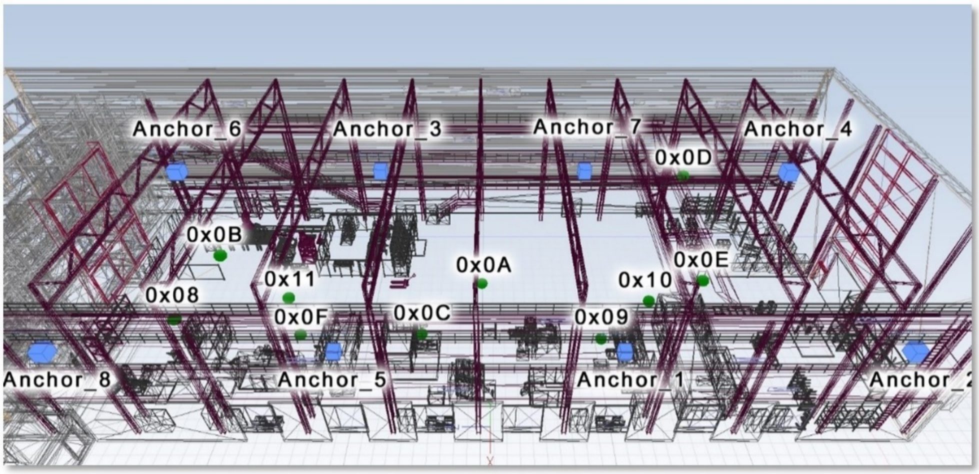

Figure 7 CAD model of the Research Factory at Fraunhofer IWU with an IIoT network (blue and green nodes)

Reconfigurability and Expandability of plant and network layout

Verbal definition of KPI: In the domain of real Industrial IoT applications a reconstruction of a facility or any change of the network (reconfiguration or expansion) causes additional costs until the network is fully operating again. The repositioning, removal or extension of devices needs to be estimated or tested before a final reinstallation. The infrastructure like power or network supplies need to be updated. Often a software reconfiguration is needed at last. To predict the impact of changes, different scenarios can be simulated before any construction work.

Way to measure KPI and data source: The time durations between the work on a real network and a simulation scenario are estimated and compared.

Quantitate KPI: Typically, the reconfiguration or expansion of a real IIoT network takes several days or weeks, based on a full time equivalent (FTE) of 8 hours per day. So, a duration between 10 and 40 working hours is a common value. The higher the impact on reorganizing the devices is, the more working hours need to be assessed for planning, installation, and software reconfiguration. So, the working hours needed to execute any change on the network layout super scales with the amount of hardware changes. In contrast to that, the reconfiguration of a simulation scenario is faster by magnitudes and can be typically done in less than one FTE. The first development of the scenario can be time consuming, depending on the software interface, but it is not considered, since the scope of the KPI is just the reconfigurability or expandability of the scenario. The only effort is to update configuration files and meta data that is used as input by the simulation models. In general, the changeability of a simulated scenario is likely up to ten times faster compared to real network installations.

Resource saving compared to real hardware testbed

Verbal definition of KPI: For real IIoT networks there are several cost items. The hardware cost increases roughly linear with each new IIoT device or peripheral hardware like cables or power supplies. Often, there is a management server or services needed that could cost license fees. Finally, the cost of staff is allocated to install and operate the network. The cost of an IIoT simulation with the NordicSim framework is only

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the amount of time a software developer or engineer must invest. There are no commercial licenses or additional hardware costs needed to work with the environment.

Way to measure KPI and data source: The cost of staff can be assumed to be the same per FTE, because for both situations highly educated staff is needed. Therefore, the main difference is the hardware invest and potential license fees.

Quantitate KPI: The simulated network is used to substitute a real testbed installation, in order to evaluate circumstances before a fully qualified real network operation. The real testbed shown in Figure 1 is such a test environment. The hardware cost of nearly 10.000 EUR for the RTLS server, eight anchor nodes, ten mobile devices and several 100m of cables and finally the cost for installation with roughly 2 FTE can be substituted completed by the simulation.

Analysis and identification of areas of improvement for Use Case 15:
The simulation of IIoT networks is not new in the research domain. Unfortunately, the integration in project planning and engineering processes is quite uncommon. The more expensive or mission critical an IIoT environment is, the more beneficial a simulation will be beforehand. Consequently, there is a need for reliable and integratable simulation models, which can be used in engineering and organizational processes. The NordicSim framework is an open source and highly expandable bundle of software packages that can be integrated into various number of software systems.

A.16Use Case 16 - Handling and assembly module

The handling and assembly demonstrator performs the assembly of printed circuit boards with electronic components. The workstation is currently operated by a company that produces lighting systems. In the workstation's current state two worker are present and each assembles half of the electronic components. A demonstrator was developed that partly automatises the workstation with the help of one industrial robot. The robot will handle half of the assembly operations of the workstation. The end result of the demonstrator is depicted in Figure 2. In order to evaluate the performance of the demonstrator, relevant key performance indicators (KPI) were identified and used.

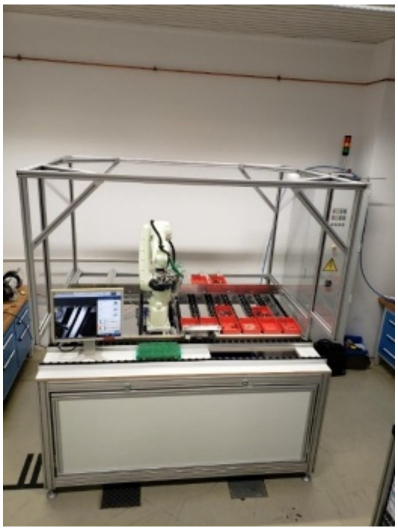

Figure 8 Handling and assembly demonstrator in the facilities of Fraunhofer IWU

Programming effort for set-up

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Verbal definition of KPI: The demonstrator needs a large amount of programming effort for the set-up. Therefore, the amount of necessary programming time is used as a KPI for our demonstrator. A distinction between the initial set-up and the integration of a new component is made. Programming time regards the robot, the handling process, the visual system, and the visual detection of the components.

Way to measure KPI and data source: The data source is based on the working hours of the robot programmer, that was responsible for the set-up of the demonstrator.

Quantitate KPI: The working hours necessary for the set-up of the demonstrator was 2 months, i.e. 318 hours. This includes robot programming, path planning, vision system set-up, component recognition and testing. In order to integrate a new component after the initial set-up, another week, i.e. 39 hours, of programming and testing is necessary until the system is able to assemble the new component reliably.

Hardware costs

Verbal definition of KPI: We calculated the overall hardware costs of the demonstrator to give possible end-users an idea, how high the initial investment of the demonstrator would be. The cost sources consist of the industrial robot, the vision system, material for the workstation which was mostly aluminium profiles, and the working hours for the assembly of the workstation. 70 working hours were needed, which do not include the programming effort. The industrial robot had a reach of 930mm, a workload of 7kg and a repeat accuracy of +/- 0,03mm. The used vision system's capabilities are considered insufficient for the assembly task, which means that for the end-use application a more expensive vision system with higher capabilities is likely necessary.

Way to measure KPI and data source: Material costs could be derived from the actual bill, whereas the costs for the robot and for the vision system are derived from the renting contract, since Fraunhofer did not by those system. The working hours for the assembly were provided by LP-Montagetechnik.

Quantitate KPI: The estimated amount of the demonstrator's hardware components is 60.000€. The costs consist of:

- 27.000€ for the robot,
- 20.000€ for the vision system,
- 10.000€ for the materials, and
- 3.000€ for 70 working hours.

Robot cycle time compared to human worker

Verbal definition of KPI: The human worker assembly times must be compared to the assembly times of the robot to get an idea of the potential of the system. Therefore, the assembly times of the robot and the assembly times of the human worker are measured and compared. To get comparable results, the assembly time of the robot is compared with the human worker time of the first workstation, since the robot only assembles half of the components, namely the components of the first workstation.

Way to measure KPI and data source: The human worker times were determined with means of methods-time-measurement (MTM) analysis. LP-Montagetechnik and Fraunhofer IWU conducted such an analysis at the workstation to measure the existing human worker times. The assembly times of the robot were measured at the laboratory of Fraunhofer IWU after the set-up of the demonstrator. The seven components

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are the point of reference for the measurements. The human worker assembled those seven components on all twelve printed circuit boards. The robot however only assembled the components on one circuit board and the average of several rounds is multiplied by twelve to make the assembly of twelve circuit boards comparable.

Quantitate KPI: 84 components need to be assembled for the 12 printed circuit boards at workstation one with seven components each. A human worker needs 340s for the assembly. To assembly the seven components of one printed circuit board, our robot took 123s. This results in an assembly time of 24,6 minutes for twelve printed circuit boards. Hence, the robot needs 434,12% of the human worker time. To state the difference the other way around, the human worker only needs 23% of the robot cycle time. Possible improvements are addressed in the closing comments.

Analysis and identification of areas of improvement for Use Case 16:
Additional closing comments are necessary to give a broader context of the KPIs' impact. The robot was not able to assemble all components that could be assembled by a human. In order to increase the number of assembled components, different gripping strategies need to be tested. The robot's movement speed during the experiments was at 50% of the total possible value. The restriction of velocity was to ensure that the components are securely handled by the vacuum gripper without detaching and threatening harm to workers during the process. Thus, a high potential in reducing the process times exist by increasing the robot's speed. Faster movement velocities, however, require additional adaptations in the gripping system in form of the vacuum gripper.

Due to the circumstance that humans were involved in the processes, the use of qualitative KPIs such as ergonomics could not be avoided. The implementation of a partly automated system enables further positive benefits in the future. These benefits cannot be measured as of right now, but they will be mentioned below. The robot did not reach the cycle times of a human worker during our experiments. It does however work continuously without the need to take personal times for shorter or longer breaks, which has to be considered as well. Due to the orientation of the components, an additional process step was necessary in the automatised process. The robot had to put the components on an intermediate fixture, to reorientate the components while picking them up again. This step leaves room for improvement for future designs of the process.

Further benefits that the use of a robot enable but cannot be measured directly are the possibility to automate the documentation process of the production line. This further enables the possibility to gather data that allows the company to integrate the processes more easily into existing digital production processes. The positives effects on the worker's ergonomic is also not measurable, but an increase in worker satisfaction and a reduction of sick leaves are possible consequences.

A.17 Use Case 17 - Artificial intelligence based stereo vision system for object detection, recognition, classification and pick-up by a robotic arm

The goal of this use-case demonstration is to automate industrial processes that involves operation with different kind of objects which are piled and with arbitrary locations. Traditionally it is hard to automate these kinds of processes because sometimes it is impossible to predetermine the positions for these objects. To overcome this issue, we develop and integrate 3D and 2D computer vision solutions with AI and robotic systems for object detection, localization and classification.

Processing time

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Verbal definition of KPI: Object detection and classification time

Way to measure KPI and data source: Processing time for the respective functionality, time measured after the data has been forwarded to the corresponding function and when it returns result.

Quantitate KPI:

Functionality	AVG time (s)	stdev (s)
Object detection	0.101	0.051
Object classification	0.0132	0.0081

Data preparation

Verbal definition of KPI: Reduced human involvement for data gathering and labelling process.

Way to measure KPI and data source: Time spent on manual work for data acquisition and preparation when data is synthetically generated.

Quantitate KPI: Data gathering and labelling process substituted by synthetic data generation, therefore reducing manual process by at least 95%

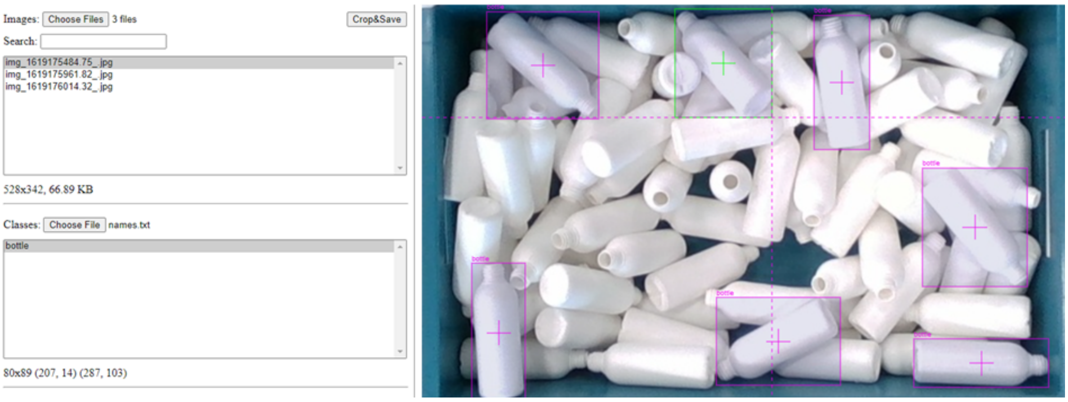

Figure 9 Manual labelling process for object detection tasks

For object detection tasks the manual labelling process includes marking each object with the bounding box as illustrated in Figure 3, but for segmentation, every pixel that belongs to the object needs to be marked. In dynamic environments, especially in the case of randomly piled objects, a lot of uncertainties and different environmental conditions can be present. Ideally, these different conditions also should be covered by the training data set in a deep learning-based object detection task to satisfy the precision requirements. However, gathering and labelling the real data is a tedious task and requires a certain amount of human resources and in some cases, it is complicated to recreate all the possible configurations. To alleviate the training data acquisition process and simplify the use of modern computer vision methods in industry, synthetic data generation is used. With the synthetic data generation approach, we intend to mimic the real data characteristics and diversify the dataset by a systematic rendering of highly realistic synthetic

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pictures. By tuning image parameters such as an object, camera and light positions, object colour or texture and surface properties, brightness, contrast, saturation, a large image diversity can be generated in resolution and level of realism depending on the requirements. For the generated data, the labels and masks, illustrated in Figure 4, are also automatically generated and therefore significantly decreasing manual work required for data gathering and labelling process. With this method the data generation can be almost fully automated. Some manual adjustments from use-case to use-case are required, whereas this manual process falls below <5% when compared to manual data labelling. In total for object detection task, manual labeling of 2200 scenes took around 80 hours, whereas for the synthetic data generation the required manual process was about 30 minutes, reducing the manual process by ~99%.

Figure 10 Scene including the plastic bottle- and the reconstructed metal can 3D models (middle) together with the corresponding depth image (left) and segmentation masks (right).

Precision of object detection

Verbal definition of KPI: Precision of object detection models trained on synthetically generated data

Way to measure KPI and data source: Ground truth - labelled data of randomly dropped objects that are overlapping each other in a pile, the precision aspects are measured on this dataset.

Quantitate KPI: At least one object with an IoU threshold above 0.95 are detected when model has been trained on purely synthetic data.

Table 1. Evaluation of object detector performance

Data distribution				**Test 1**			**Test 2**		
Real	**Synthetic**	**Real/ Synthetic Ratio %**		**Step**	**AP @0.5:0.95**	**OD %**	**Step**	**AP @0.5:0.95**	**OD %**
8800	0	100	0	9100	88.61	100	9100	69.22	96.95
7920	880	90	10	7900	88.61	100	9200	71.04	98.47
7040	1760	80	20	6000	88.36	100	8000	73.23	100
6160	2640	70	30	6300	**88.65**	100	7600	72.83	100
5280	3520	60	40	6900	88.22	100	7400	72.5	100
4400	4400	50	50	4400	85.82	100	5000	**73.84**	100

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3520	5280	40	60	8000	85.59	100	8700	70.27	100
2640	6160	30	70	7200	84.39	100	5900	64.57	100
1760	7040	20	80	7200	84.23	100	4500	63.62	100
880	7920	10	90	8200	82.59	100	7000	63.25	100
0	8800	0	100	7700	70.01	100	5000	38.66	100

The performance was evaluated on the test datasets which consist of real data. For each of the acquired images in the test datasets, the positions of the bottles were altered. The intensity of lightning and camera exposure time was systematically modified to acquire a high diversity of different lighting conditions. Two test datasets were gathered and manually labelled, first dataset Test 1 was captured with Intel RealSense camera, however, Test 2 was captured with different camera - Zivid.

Figure 11 Test 1 dataset

Figure 12 Test 2 dataset

Object detector evaluated on data closer to real training data *Test 1* (acquired by the same camera as the data on which the AI model was trained) scored similar average precision results when real data amount was higher than synthetic data as depicted in Fig. 5(a). This also holds true for higher IoU threshold values from 0.85 to 0.95. All the trained models showed similar average precision results in the IoU threshold region from 0.5-0.8. The main difference can be seen in the case when the model is trained on purely synthetic data, as the precision slightly decreases.

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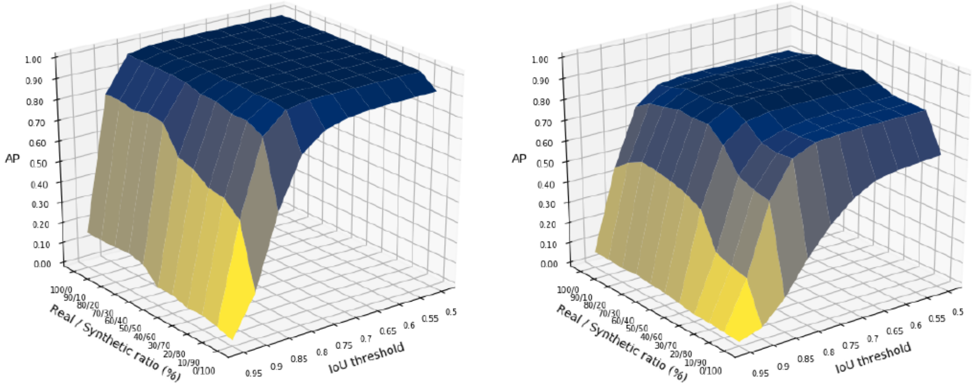

(a) Test 1 (b) Test 2

Figure 13 Average precision of object detection models on real images over different IoU thresholds, viewed by the ratio of real to synthetic data in the training datasets

A different situation can be seen when the object detector is evaluated on a test dataset that contains different environmental parameters – *Test 2*. In this case the synthetic data supplements real data and increases average precision, whilst achieving the highest precision on a 50/50 ratio. Similarly, as with the evaluation results on *Test 1* dataset, also in this case object detector trained on purely synthetic datasets showed the least precision. Even though the object detector trained on real data or different combinations outperforms the detector trained on purely synthetic data, the main precision aspects in this task are connected to the specific use case criteria. Respectively, the KPI is to detect at least one object in the scene with an IoU threshold above 0.95. Obtained results on this aspect are depicted in Table 1 under columns Object Detected (OD). On both test datasets, the trained models could meet this requirement, except in Test 2 case, when the model was trained on purely real data and in following 90 / 10 ratio, which shows that the KPI has been successfully achieved.

Analysis and identification of areas of improvement for Use Case 17

The proposed TRINITY use-case demonstration: AI-based stereo vision system deals with the uncertainties of the environment by use AI for object detection, recognition and classification in conjunction with robot control that includes dynamic trajectory generation to avoid obstacles and successfully complete pick & place tasks in the dynamic environment. The system can be trained to detect and estimate the grasp pose of different objects that are randomly distributed in a pile, therefore, enabling automation of industrial processes involving a different kind of objects with unpredictable positions. It has been developed with a focus on the scenario, where bottles and cans are being sorted, however, the Use Case and its modules can be adjusted to different scenarios and different industries by usage of ROS and modularity of the system. The functionalities of the object detection module could be improved by increasing the flexibility to the object types as the system is limited to estimating the grasp pose for longitudinal and symmetrical objects.

A.18 Use Case 18 - Rapid development, testing and validation of large-scale wireless sensor networks for production environment

The demonstrator showcases a factory digitalization solution bringing predictive maintenance to the non-digitalized factory while minimizing the costs and factory downtime by using infrastructure as a service approach. Using the infrastructure as a service the sensors necessary for predictive maintenance can be seamlessly integrated and validated in the factory. We are using the EDI WSN/IoT TestBed as infrastructure

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as service which provides the ability of large-scale sensor network deployment and additional debug features such as energy consumption monitoring etc.

Initial deployment cost for evaluation

Verbal definition of KPI: Investment necessary to test the envisioned idea and evaluate the added value of the solution.

Way to measure KPI and data source: Calculate the cost of EDI WSN/IoT TestBed usage as Infrastructure as a Service vs off the shelf systems available for purchase. Any custom-made solution would exceed the cost of the off the shelf system, so this comparison is considered the worst-case scenario in case of the KPI evaluation. We assume the simple need of 10 temperature and relative humidity sensors in the deployment site.

Quantitate KPI: The estimated cost by using an off the shelf system are as follows:

- Base station 490€
- 10x T/RH sensors 80€, total 800€
- Cloud subscription 90€

This brings the total cost of the off the shelf components up to approximately 1380€. For a one-month period the needed 10 EDI WSN/IoT TestBed workstations can be used for approximately 500€.
This comparison assumes that the manual work for setup of the system is similar, so it does not need to be included in the calculation.

System reconfiguration time

Verbal definition of KPI: Time necessary to remotely reconfigure the deployed system, excluding the preparation of the update.

Way to measure KPI and data source: Measure the system downtime while the necessary configuration updates are being applied while using EDI WSN/IoT TestBed as Infrastructure as a Service vs off the shelf system available for purchase.

Quantitate KPI: The EDI WSN/IoT TestBed workstation applies the update in approximately 1 minute, this process can happen parallelly on all workstations. The evaluated off the shelf system does not provide a way of updating the system configuration remotely.

Analysis and identification of areas of improvement for Use Case 18:
The proposed TRINITY use-case demonstration Rapid development, testing and validation of large scale wireless sensor networks for production environment deals with the ongoing problem of cost and time expenditure in the factory digitalization process allowing for rapid prototyping of the envisioned solution with severely reduced costs for the hardware and backend system development by providing a semi plug & play IoT system as Infrastructure as a Service ready to be deployed in the production environment without the need of extensive downtime typically necessary when changing the whole equipment. The developed demonstration can be improved by providing a wider range of available hardware to expand the available plug & play scenarios

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