SPECIFICATION OF FAIRWORK USE CASE AND DAI-DSS PROTOTYPE REPORT

D2.1

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EXECUTIVE SUMMARY

Deliverable D2.1 specifies the design requirements for the first relevant stage in the Horizon Europe project FAIRWork aiming at fair decision making within complex systems in the production domain. From the planned use cases of the industrial partners - FLEX “Automated Test Building”, “Worker Allocation”, “Machine Maintenance After Breakdown” and CRF “Workload Balance”, “Delay of Material” and “Quality Issues” - the report constitutes and specifies the basic design decisions for research and development directions in the project. A major contribution is the provision of the initial architecture of an innovative service framework for decision support systems.

The first part of the report is dedicated to the design thinking approach as an efficient choice for the analysis of user requirements. The planned use case scenarios were primarily examined from a user-driven perspective. In several workshops a participatory process was applied in order to deduce the most substantial design decisions from the results of the highly interactive sessions. A model-based approach of the design process was chosen in order to determine the user requirements that were consequently defined and described in detail. In this way, the knowledge about a use case was externalised in the form of conceptual representations, using domain-specific modelling languages that are suitable and provide the required construct for representation and processing. In a further step, the high-level scenarios were designed in a collaborative, interactive, and agile environment involving experts from different backgrounds. Processes are the outcome of this structured approach requiring support for: “finding similar projects”, “find relevant experts”, “simulate production process”, “allocate worker”, “map workers with profiles”, “find similar problems”, “reschedule production line”, “allocate order to production line”, “assess the impact”.

In the second part, we give an **overview about the key challenges** of FAIRWork. In the current production industry there is a need to make the current automated and hierarchical structured production processes more flexible. At the same time digitalization with AI support is seen as a key enabler for more energy efficient and resource efficient services, products or business models, by also enabling process optimization in the overall production process. Therefore, we describe in more detail the main challenges technical challenges such as configuration, resource allocation, and selection aspects. These three challenges are highly relevant for making the process more flexible, adaptive, and resource efficient by using the relevant AI-based decision strategies in our complex distributed decision-making. At the end, the trustworthy AI aspect is a further key challenge to get AI accepted by the involved humans and also utilize its potential.

In the third part, the **overall methodology of making complex decision-making is outlined**. Within this chapter, we describe the overall procedure for implementing complex decision-making processes. Therefore, this chapter gives an overview about relevant concepts for the research direction and implementation of such complex decision making by using AI services. In FAIRWork, AI is used in all our scenarios to automate processes or to make their processes more resource-efficient. Since humans are an important part of the overall decision process, trust in AI and human factors plays an essential role, therefore these aspects are explained. Finally, the technical concepts for a concrete implementation such as digital knowledge base, digital twin, digital shadow, will be discussed as well. Finally, it follows the explanation about the orchestration of decision-making processes by using Microservices.

In the fourth part, the initial architecture of the project is presented based on the overall project objectives and requirements. Key components of the FAIRWork service framework are motivated, described, and their relevant features are presented. A detailed description of these components is given in Deliverable D4.1 including the technical implementation of the basic core services or application specific services.

Finally, the initial design of the FAIRWork’s architecture is compared with most relevant technical architectures that are commonly used in the industry environment domain, such as, Gaia-X, FIWARE, International Data Space, and RAMI.

PROJECT CONTEXT

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Task	T2.1, T2.2
Dependencies	WP3, WP4, WP5

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1 INTRODUCTION

1.1 Purpose of the Document

This document specifies the design requirements and the initial architecture of a service framework for platform within the Horizon Europe project "FAIRWork" and complex fair decision making within production domain. A further important purpose of this deliverable is to constitute and specify the basic design decisions derived from the planned use cases as described in the work description.

Within the project, we want to transform the decision making of current production processes towards a cooperative decision-making, by:

- introducing concepts that make human workers trust the decision making independently of whether the decision is performed by a human, by an AI, or in a hybrid manner,
- enabling cooperative decision-making to capture the real world situation in a more complete and holistic way, and
- introducing more influence factors to transform the current automated and hierarchical system towards cooperative networks with individual responsibilities and competences.

The production process is the central knowledge platform and starting point, when analysing which – conflicting or relevant – “decisions” need to be taken, by whom, with which information and for which goal. We support human decision makers in making decisions (a) under uncertainty, (b) strong dependencies on unknown future events, (c) affecting human and machines work balance, (d) affecting the overall success of the production process, (e) using with “best effort” the available data in (f) often a very complex and conflicting situation.

1.2 Project Introduction

Manufacturing companies are more vulnerable than ever to international competition in the modern world due to advancements and incorporation of Digital technologies like AI and Robotics in production lines. Different objectives can be used for production system optimization. They might cover all technological components, including the use of robots, machines, AI, or they can apply to the improvement of processes and systems using important criteria like the number of workers, the number of stations, the line's balance between stations, and others. All these criteria may be employed in the optimization process to govern the process depending on some decisions.

All optimization tasks need evaluation of performances of process, machines, workers. The most common way used in most of the manufacturing companies to evaluate the production systems are Key Performance Indicators. These indicators show the performance of the process in all needed aspects. These indicators in business have the preferable value which is a target of process performance. Decisions are made based on these measurable performance indicators to control the process due to cost, expected efficiency and energy consumption. A main challenge is that often these decisions overlap or are in conflict to each other.

Most of the production process are complex, thus there is a high likelihood that the decisions made lead to unwanted result. Additionally, decision-making in the modern production environment results in a great deal of uncertainty due to lack of knowledge about something or lack of precision data. It is crucial because, in the case of complicated production processes, the choice about the process' desired performance is not clearly stated. This makes it difficult to determine with precision if a method's assistance can provide managers with the chance to grasp the situation's entirety and base decisions on objective information. Based on the situation presented above, making a fast and good decision is important to make the profitability and effective business in the world of customization and short lead times.

Current automated and hierarchically structured production processes can only insufficiently deal with the upcoming flexibilization. To tackle this complex production setting we are introducing a decentralized AI system by "democratization" of decision making in production processes, where all relevant stake holders are involved. The proposed Democratic AI-based Decision Support System (DAI-DSS) democratically finds the appropriate decision for a concrete situation during production. Each human or technical actor is represented by an agent who negotiates based on the status provided by the digital shadow and twins. The future situation is predicted by AI algorithms for each individual actor considering the modelled knowledge base that defines each negotiation strategy. A multiple optimization algorithm finds the most appropriate solution considering the needs of all involved human and technical stakeholders.

In the FAIRWork project two use cases, CRF and FLEX, have been selected, both providing a complex combination of human, AI, robots and data, acting as a role-model for flexibilization and optimization of production processes and aiming to consider energy efficiency and workforce safety, production efficiency, and workload management in their decision making. The two use cases with complex cyber-physical smart and data driven processes are:

(1) **The car manufacturer CRF** needs to optimize the throughput between two succeeding production lines where automatic production lines in a press shop, static and mobile robots, and human workers with and without machines are cooperatively working together.
(2) **The electronic manufacturer FLEX** wants to speed up and improve the programming of manufacturing robots for low volume production. The cooperative production by humans and robots is influenced by factors like energy consumption for robot movements, machine hours, safeness of cooperating workers within the co-working area, selection, and tooling of grippers in combination with the production plan and the required flexibility in low volume production.

To address the issues in the use cases the FAIRWork will use the proposed Democratic AI-based Decision Support System (DAI-DSS) to optimize the production process. The overall objective of the DAI-DSS is shown below:

Democratic AI-based Decision Support System (DAI-DSS) - Objectives:

- **Speed-Up the Configuration of complex Decision-Making:** Models speed up the configuration and maintenance.
- **Enable Compliance in Decision-Making by approved Models:** Using methods and tools to approve decision models
- **Improve the Co-creation Capabilities:** Using physical laboratories enabling participatory and user-centred design.

The FAIRWork project brings "Human, AI, Data and Robots" together, by introducing: (a) Design Decision Models and assess if those models are "appropriate / fair", (b) decentralize the decision-making, by representing involved – human or technical – actors within a Multi Agent System and configure each agent with previously approved decision models, (c) broaden the view to optimize the production process, by also introducing social and energy related parameters to the existing technical and business related aspects. These will be identified and valuated in a participatory and user-centred design process. This enables a more balanced decision-making in complex situations, as the flexibility opens-up "space for maneuverer".

The goal is to change the present production process's decision-making to cooperative decision-making so that human workers may trust the decisions made regardless of whether they were made by humans, artificial intelligence (AI), or in a hybrid fashion. The DAI-DSS focuses on providing support for making decisions in the production process under uncertainty, strong dependencies on unknown future events, affecting the balance of work between humans and machines, and affecting the overall success of the production process while using the available data with "best effort" in a very complex and conflicting situation for human decision makers.

1.3 Document Structure

Chapter 2 is dedicated to the **design thinking approach** as an efficient choice for the **analysis of user requirements for FAIRWork**. A key part of this work is to collect and describe the complex decision making processes within the targeted use cases. The planned use case scenarios were primarily elaborated by applying a user-driven perspective. In several workshops, a participatory process was applied in order to deduce the most substantial design decisions from the results of the highly interactive sessions.

Afterwards, a model-based approach of the design process was chosen in order to analyse the user scenarios in a structured way. In this step, the knowledge about a use case decision-making process was externalised in the form of conceptual representations, using domain-specific modelling languages that are suitable and provide the required construct for representation and processing. The high-level scenarios were elaborated in a collaborative, interactive, and agile environment involving experts from different backgrounds. Outcome of this structured approach are the processes.

In chapter 3, we give an **overview about the key challenges** of FAIRWork. In the current production industry there is a need to make current automated and hierarchical structured production processes more flexible. At the same time digitalization with AI support is seen as a key enabler for more energy efficient and resource efficient services, products or business models, by also enabling process optimization in the overall production process. Therefore, we describe in more detail the main technical challenges such as resource mapping and configuration, resource allocation, and resource selection aspects. These three challenges are highly relevant for making the process more flexible, adaptive, and resource efficient by using the relevant AI-based decision strategies in our complex distributed decision-making. At the end, the trustworthy AI aspect is a further key challenge to get AI accepted by the involved humans and utilize its potential.

In chapter 4, the **overall methodology of making complex decision-making is outlined**. Within this chapter, we describe the overall procedure for implementing complex decision-making processes. Therefore, this chapter gives an overview about relevant concepts for the research direction and implementation of such complex decision making by using AI services. In FAIRWork, AI is used in all our scenarios to automate processes or to make their processes more resource-efficient. Since humans are an important part of the overall decision process, trust in AI and human factors plays an essential role, therefore these aspects are explained in detail. Finally, the technical concepts for a concrete implementation such as digital knowledge base, digital twin, digital shadow, will be discussed as well. Finally, it follows the explanation about the orchestration of decision-making processes by using micro-service.

In chapter 5, an **outline of the initial architecture of the project** is given based on the overall project objectives and requirements. Key components of the FAIRWork service framework are motivated, described and their relevant features are presented. A detailed description of the initial architecture is given in Deliverable D4.1 including the technical implementation of the basic core services or application specific services.

In the final chapter, the initial outline of FAIRWork's architecture is compared with relevant other initiative and their architectures that are commonly used in the industry relevant domain, such as, Gaia-X, FIWARE, International Data Space, and RAMI. There, we also point out the missing components for complex decision making in these initiatives.

2 USER REQUIREMENT ELICITATION USING DOMAIN MODELS

In this chapter, the user requirements are introduced using domain models. Following a model-based approach, a FAIRWork specific methodology has been developed and applied at the use-case partner sites. In the following section, the methodology is briefly introduced, followed by the outcome discussion.

2.1 Design Methodology for Decision Process Design

As a general characteristic, the design process in FAIRWork follows a model-based approach. This encompasses that the knowledge about a use-case is externalized in the form of conceptual representations applying domain-specific modelling languages that are adequate and provide the required construct for representation and processing. The decomposition is performed as a formalisation process – high-level scenarios are designed in a collaborative, interactive and agile setting involving expert stakeholders from different background.

The joint grouping and evaluation and assessment of these scenarios triggers either an interaction on scenario level or a decomposition to process representations and technical architectures. The OMiLAB infrastructure available within the project is utilized during these sessions. The following Figure **1** shows the methodology developed for FAIRWork graphically and each phase is briefly introduced.

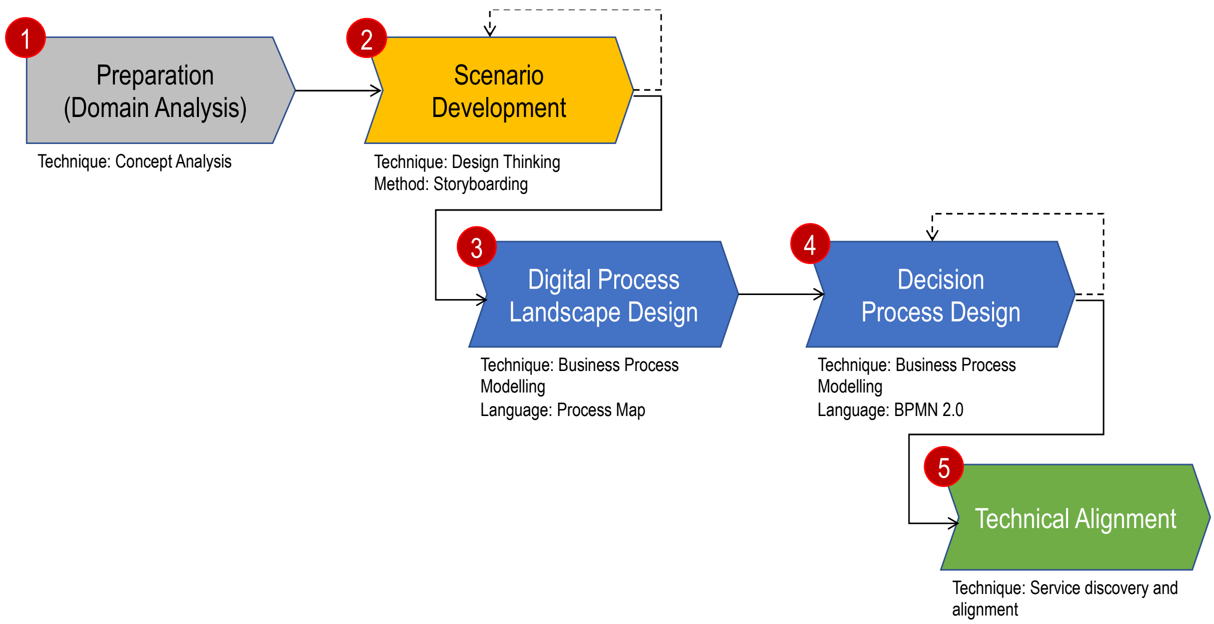

Figure 1: Design Methodology for Decision Processes

The methodology is constructed using a loose coupling approach. This means that the selected method/technique for each phase can be exchanged according to use case requirements. The selected steps for FAIRWork use cases are introduced:

1. **Preparation:** the preparation phase is concerned with the identification of concepts that are required to represent the scenarios. This is driven by the domain-specific and project requirements. In this context, domain-specific is understood as the industrial sector, whereas project-based requirements are derived from the objectives of FAIRWork. The outcome of this phase is a visual design library that is adequate and relevant for the on-site stakeholder workshops. On these on-site workshops the involved stakeholders will use and understood the pre-pared visual design vocabulary.

Method: Concept Analysis
Tooling: Text Analysis

2. **Scenario Development:** scenarios are realized in a joint effort using the Scene2Model[1] approach. During design thinking workshops run on-site and remotely, storyboards represent the abstract use case descriptions. The objective during this phase is to understand the case and analyse it from various perspective (relevance, applicability) without limiting the creativity through formalisation.
Method: Storyboarding
Tooling: Digital Design Thinking using Scene2Model
3. **Digital Process Landscape Design:** the digital process landscape represents the high-level view on the use case from a value-chain perspective. The end-to-end processes are evaluated using process mapping on an abstract level. Utilizing a template-based approach, a best-practice digital process landscape from the production industry is specialized and adapted for the specifics of the use case partners. The best practice is the result of project results within the target companies, abstracted and provided as a reference model.
Method: Business Process Modelling
Tooling: ADONIS[2]
4. **Decision Process Design:** as a breakdown and detailing of the landscape, selected processes are modelled using the BPMN 2.0 standard. Selecting BPMN as a standard enables knowledge sharing and standardized representation of decision processes. The standard is elevated with concepts required for decision design such as performance indicators/success factors and technical infrastructure identification.
Method: Business Process Modelling using BPMN 2.0
Tooling: ADONIS
5. **Technical Alignment:** the alignment of technical services, specifically AI services is started based on the process design in step 4. We consider this phase as continuously evolving depending on the dynamic of the available AI services, the dynamic of the application scenario, as well as the lessons learned.

2.2 Application Scenarios and Use Cases at FLEX

This application user scenarios focuses on decision support at the production lines at FLEX. Here humans and robots work together to create products for the customers. Pictures of robots, which are used in the production process of FLEX can be seen in Figure **2**. These robots can be configured to accomplish different tasks within the production process and are able to work alone or together with human workers.

[1] https://www.omilab.org/design-thinking
[2] https://www.boc-group.com/en/adonis/

Figure 2: Example Pictures of Robots, used in the Production Process at FLEX

Figure 3 introduces the three use cases at FLEX as the three columns: (a) FLEX Automated Test Building, (b) FLEX Worker Allocation, (c) FLEX Machine Maintenance after a breakdown.

Each of the models in the first so-called "Scenario Design" layer can be accessed by following the link within the modelling environment (expressed in Figure 5, Figure 6 and Figure 7).

The second layer represents the processes that describe high level scenarios in more detail using BPMN. Each process, including the sub-processes of the "Process" layer can be accessed following the link within the modelling environment (expressed in Figure 9, Figure 10, and Figure 11.

The third layer represents the availability of various AI technologies, which can be used to support the decision making described in the different scenarios and processes. The same AI Pool is available for all scenarios, but not all AI technologies are used for every use case. A modular approach should enable to map suitable AI services to the different types of decision challenges.

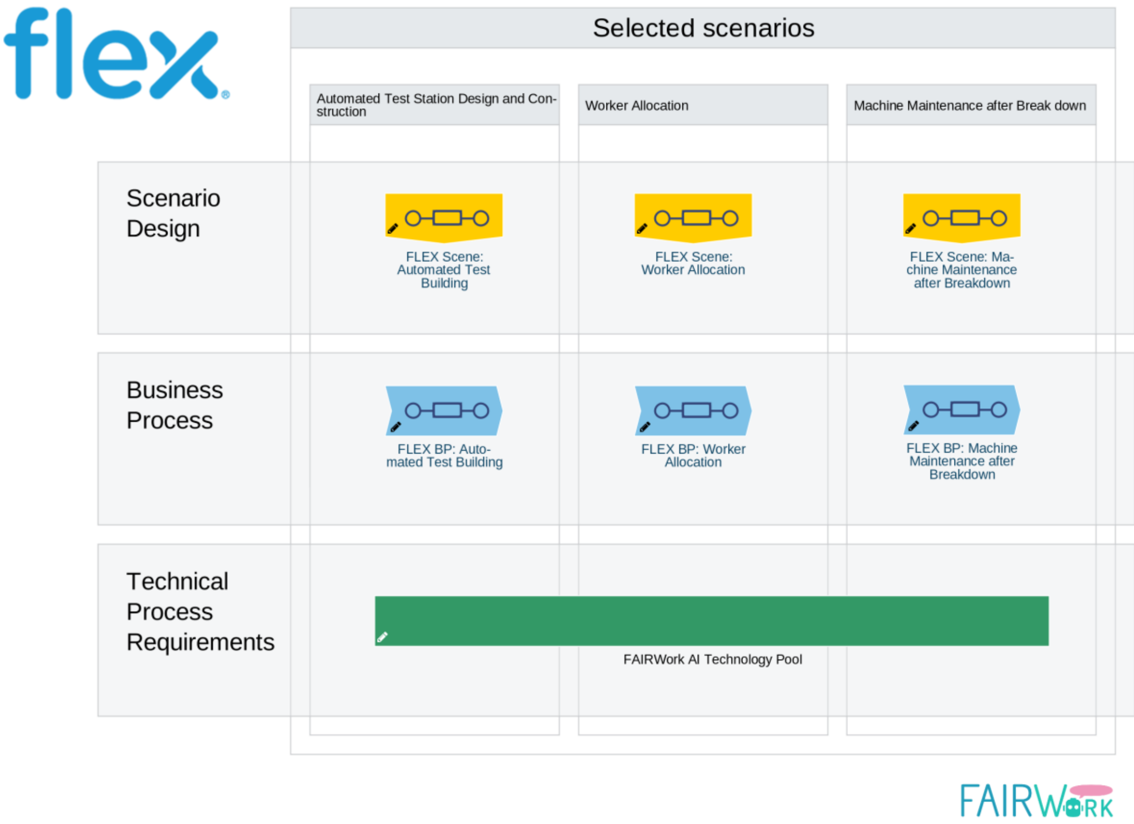

Figure 3: Alignment of Scenario Design with AI Technology

2.2.1 Creating Scenario Design using Design Thinking

Figure 4: Design Thinking Workshop at FLEX

Based on on-site visits and design thinking workshops with the domain experts, we could extract three scenarios describing the interaction for:

(a) FLEX Automated Test Building,

(b) FLEX Worker Allocation, and

(c) FLEX Machine Maintenance After Breakdown.

Figure 4 shows the design thinking workshop at Flex using customized Scenes for Scene2Model, Flip Charts and Power Point presentations.

The result were three scenes, one scene for each scenario. Each scene is described in more detail below.

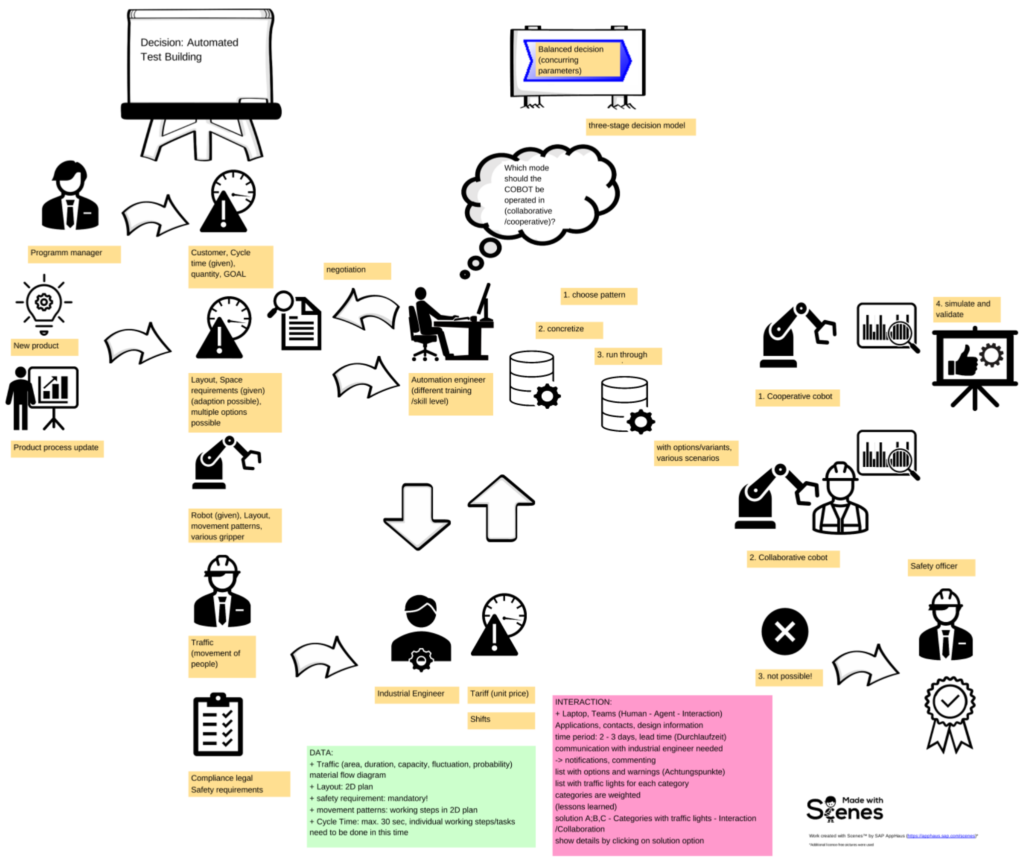

Figure 5: Scene Scenario - FLEX Automated Test Building (full size image at Annex A.2)[3]

Scenario 1: FLEX Automated Test Building

The automated test building scenario for a robot cell and the connected production process is described in the first scene, depicted in Figure 5**Fehler! Verweisquelle konnte nicht gefunden werden.**.This scenario occurs during the design phase and begins with a new product order or the need for a production process update. This information, along with order details (e.g., required cycle time, quantity, customer details), is provided by the program manager and forwarded to the automation engineer, who is in charge of planning and designing the robots' inclusion in the production process for a specific order. A robot can operate in two modes: cooperative mode and collaborative mode, with the former being the preferred option. Because no humans are involved or standing nearby in cooperative mode, the robot can move faster, allowing for a shorter cycle time. In collaborative mode, a human works closely to or with a robot, and the robot's speed must be reduced for safety reasons if a human enters its range of motion.

Several factors must be considered during the robot's design process. Aside from cycle time, the layout of the production hall in which the robot will operate is critical. There could be several options for where to place the robot, including modifying the layout (e.g., adding additional barriers for safety reasons). The robot itself introduces new factors into the design process, as it must be determined which movement patterns can be programmed and which gripper should be used. Additional space may be required depending on the movements of the robot. Human traffic in the production hall is also important because the robot must slow down whenever a human enters its operation radius, and if a human has a working station nearby, only a collaborative mode is possible. Of course, safety requirements are also important and must be considered. All of this information must be gathered by the automation

[3] Work created with Scenes™ by SAP AppHaus (https://apphaus.sap.com/scenes) and licence-free images

engineers, which necessitates collaboration with other stakeholders (e.g. the industrial engineer knows about the different shifts and how much traffic is created or what the current tariff – unit price is).

Automation engineers have varying skill levels because some have more experience than others or have attended more trainings. Automation engineers with lower skill levels require more assistance during the design phase, but the general design process always follows the same steps. Choosing design patterns from a catalogue can be a good starting point for the engineering project, but the draft must then be concretized. Adding details to the project can result in a variety of design options. Looking at similar projects that have been successfully completed in the past or simulating different design possibilities to compare them to one another may be helpful in finding a solid solution. Providing checklists could help the engineer to consider all relevant aspects of the project. Contacting more experienced engineers for assistance may also be an option for decision support during a design phase. Finally, the output could be a cooperative robot project, a project where only the collaborative mode is practicable, or a project that is not feasible at all.

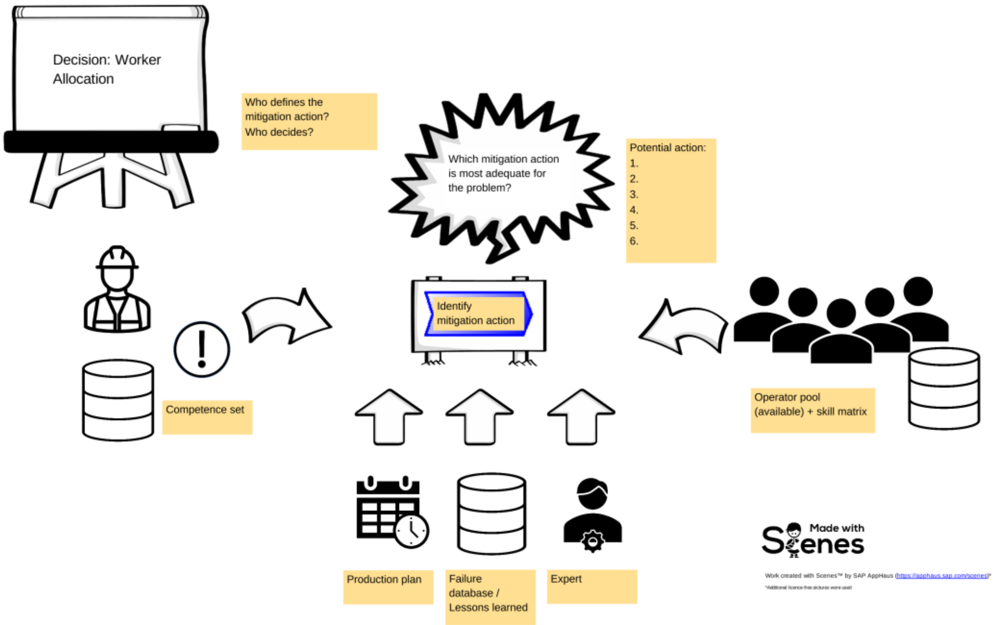

Figure 6: Scene Scenario - FLEX Worker Allocation (full size image at Annex A.4)[4]

__Scenario 2: FLEX Worker Allocation__

The second scenario concerns worker allocation and the corresponding scene is shown in Figure 6. Allocating workers is required either before the shift begins (for example, if a worker calls in sick) or during operations (e.g., worker cannot continue to work because of some incident). The challenge in both cases is determining the appropriate counter-actions (e.g., finding a suitable replacement for the missing worker, shifting orders in the production plan). The first step in finding a suitable replacement is to see who is currently available and who has the necessary training to operate the machine. Every machine has a "screenplay," which describes what they are capable of and what operators need to be trained for. This data is saved as a competence set and can be obtained from Human Resources Management. Workers' preferences for operating specific machines in specific production halls or at specific times could be added to her skill book. In addition, replacement actions should be consider “fairness” in the sense that not always the same workers are affected from the mitigation actions (e.g. working longer shifts, increased workload).

Aside from the worker's abilities, the production plan must also be considered. The priority of certain orders can influence the decision of which workers can be removed from their current position to help out where needed without

[4] Work created with Scenes™ by SAP AppHaus (https://apphaus.sap.com/scenes) and licence-free images

causing too much damage. Not only should a simple swap between two workers be considered, but so should the swapping of multiple employees. This scenario's output should provide an overview of potential candidates for a replacement action. Depending on the urgency of the replacement decision, running a simulation to compare the various candidates could provide additional insights into the impact of changing worker assignments on the business factors.

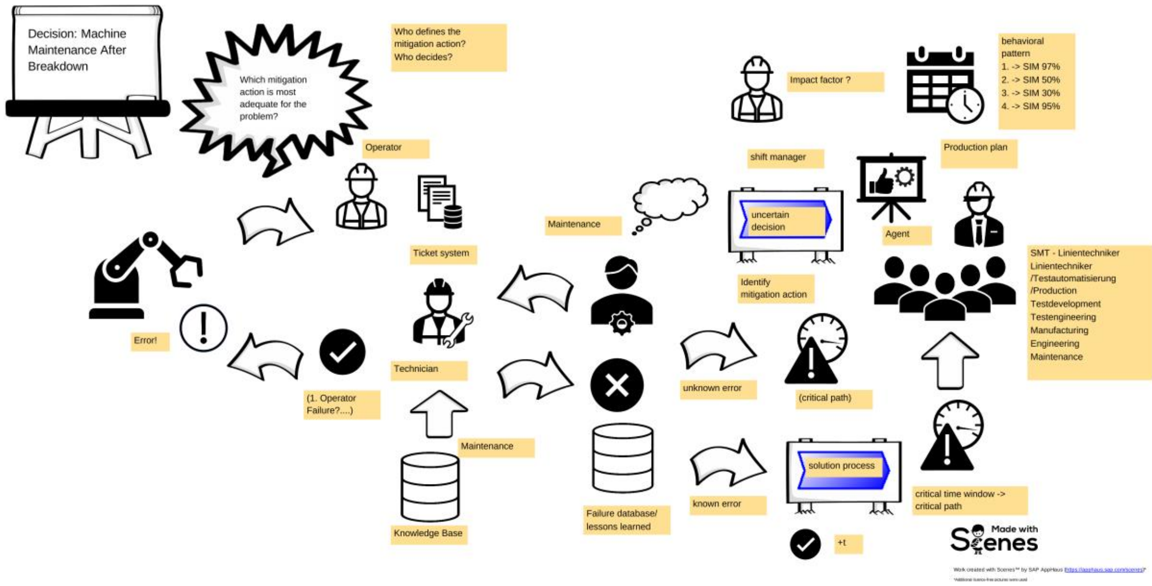

Figure 7: Scene Scenario – FLEX Machine Maintenance After Breakdown (full size image at Annex A.6)[5]

Scenario 3: FLEX Machine Maintenance After Breakdown

The third scenario involves a machine breakdown and the subsequent maintenance steps. This scenario is represented as a scene in Figure 7. When a machine fails, a ticket is created in the ticket system. A technician will arrive at the machine to determine whether it is a simple operator error or a technical error. If it is an operator failure, the problem is easily solved; otherwise, the failure database must be checked to see if it is a known problem. Known issues have occurred in the past or are identifiable via the error code and they are solved by triggering the corresponding solution process.

Because some technical problems are more complex and take longer to solve (e.g., spare parts must be ordered, longer repair work), they risk exceeding a critical time window and disrupting production. If a new error occurs, all available technicians from various teams or departments (e.g., engineering, maintenance, etc.) collaborate to identify mitigation actions. In this case, the time required to solve the problem is unknown, and the critical time window is very likely to be exceeded as well.

Countermeasures (e.g., shifting to another production line, using different machines, etc.) must be evaluated in both cases, taking into account order priorities and available worker and machine capacities. A summary of potential alternatives should assist the decision maker. If time allows, running simulations to show the impact of selecting a specific option could help with decision making.

[5] Work created with Scenes™ by SAP AppHaus (https://apphaus.sap.com/scenes) and licence-free images

2.2.1 Detailing Application Scenarios with Processes

First, we started with a high-level company map that provides an overview of all relevant processes of the organization. Based on standard company maps for the industry sector, we customized the map to describe the process map of FLEX (Figure 8).

Then the processes that should be supported by the decision support system has been highlighted. In case of FLEX it is the **Scheduling**, **Rescheduling Operator** and **Machine Allocation** as well as **Test Automation Configuration**.

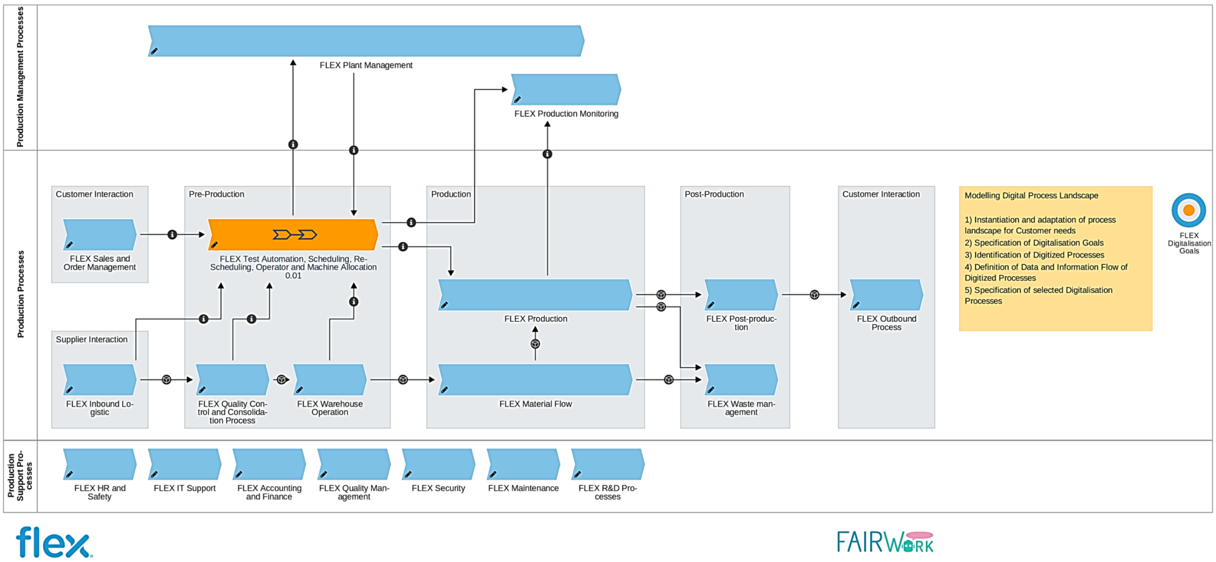

Figure 8: FLEX Process Map (full size image at Annex A.1)

The identified process from the process map is defined in more detail using Process Notation.

Process Scenario 1: FLEX Automated Test Building

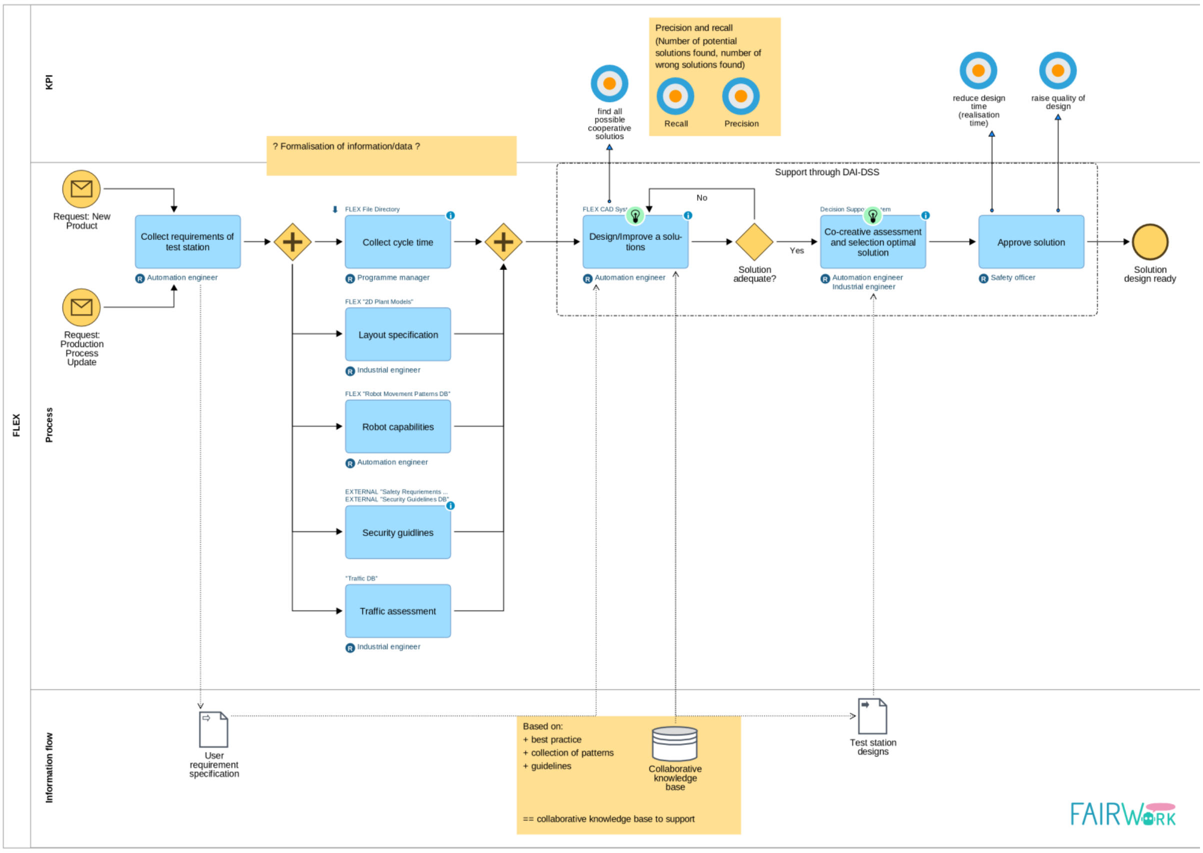

Figure 9: FLEX Automated Test Building Process (full size image at Annex A.3)

Figure 9 describes the process for automated test building. First, the order is analysed and then the different interactions for (a) the requested cycle time, (b) the layout specification, (c) the robot specification, (d) the security guidance, and (e) the plant traffic assessment are worked out.

Then a creative design phase in iterations is executed, where the domain experts design the intended solutions, and uses tools for simulation and analysis to verify if the solution is ready for the shop floor.

In most of the cases different alternatives will be worked out, that are then co-operatively assessed to select the optimal solutions. After the approval of the solution, the test robot design is handed-over to the shopfloor.

The decision-making process was analysed in detail during several meetings with FLEX, including an on-site meeting with requirement engineering applied by OMiLAB, BOC and JR. The Figure 5, Figure 6 and Figure 7 depicts a schematic sketch of the resulting description of the decision-making structure reflecting the configuration process to classify and determine the collaborative robot setting in the configuration within a predefined production process.

The decision-making process is initiated either with a request for a new product or with the request for an update of the production process. In direct response, and as a first step, the automation engineer will collect requirements of the test station. This extensive process would include (1) to contact the programme manager to report about targeted cycle time as a result of the human-robot interaction, (2) to query the industrial engineer about the layout specifications, (3) to ask the automation engineer to define the required robot capabilities, (4) to determine the security guidelines according to the automation engineer and further responsible staff, and (5) to receive details in terms of the traffic assessment by the industrial engineer. The automation engineers would integrate these requirements and boundary conditions into a list of potential solutions, including the design and improvement considerations with respect to an existing solution that needs to be updated. Here we identify a highly relevant point of assistance service in terms of intelligent decision support. The automation engineer needs a collection of all possible cooperative solutions ranked with respect to expected return of performance and security concerns. The number of potential solutions found as well as the number of wrong solutions found will then be applied to determine recall and precision of the intelligent decision support system. The automation engineer would interact herself with the proposed solution space and in this context a co-creative assessment would emerge, eventually finalising in a selection of the optimal solution. A final review of the safety officer would inspect this solution with respect to the quality of design and cooperate in reducing the design time, eventually approving the cooperative solution process.

Process Scenario 2: FLEX Worker Allocation

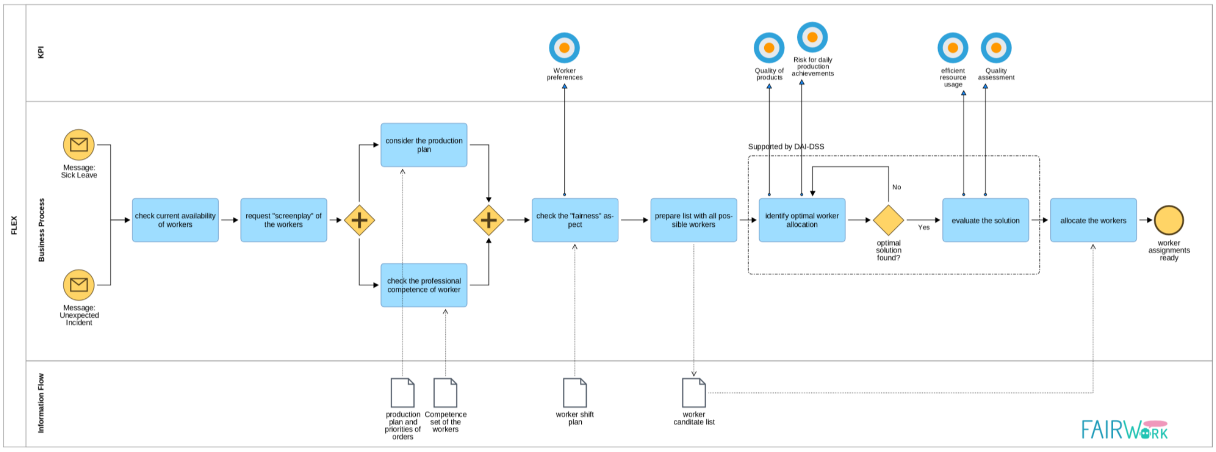

Figure 10: FLEX Worker Allocation Process (full size image at Annex A.5)

The process of the scenario 2 “FLEX Worker Allocation” is illustrated in Figure 10. It starts by receiving a message that a work shift is cancelled due to a sick leave or another unexpected incident. The first step is then to check current availabilities of workers whose skills maps to the required ” screenplay”. The competences of the workers are compared with the minimum requirements. At the same time production plan must be considered. Furthermore, it is important to evaluate the fairness aspect and include employee preference aspects into the reallocation considerations. Then a list with all possibilities is prepared and an optimal worker allocation is defined. This activity should include risk evaluation for not achieving production goals and check whether quality standards of the products can be fulfilled or not. Is an optimal solution found, it must be evaluated on efficient resource usage and its quality. The last step is to reallocate the workers.

Process Scenario 3: FLEX Machine Maintenance After Breakdown

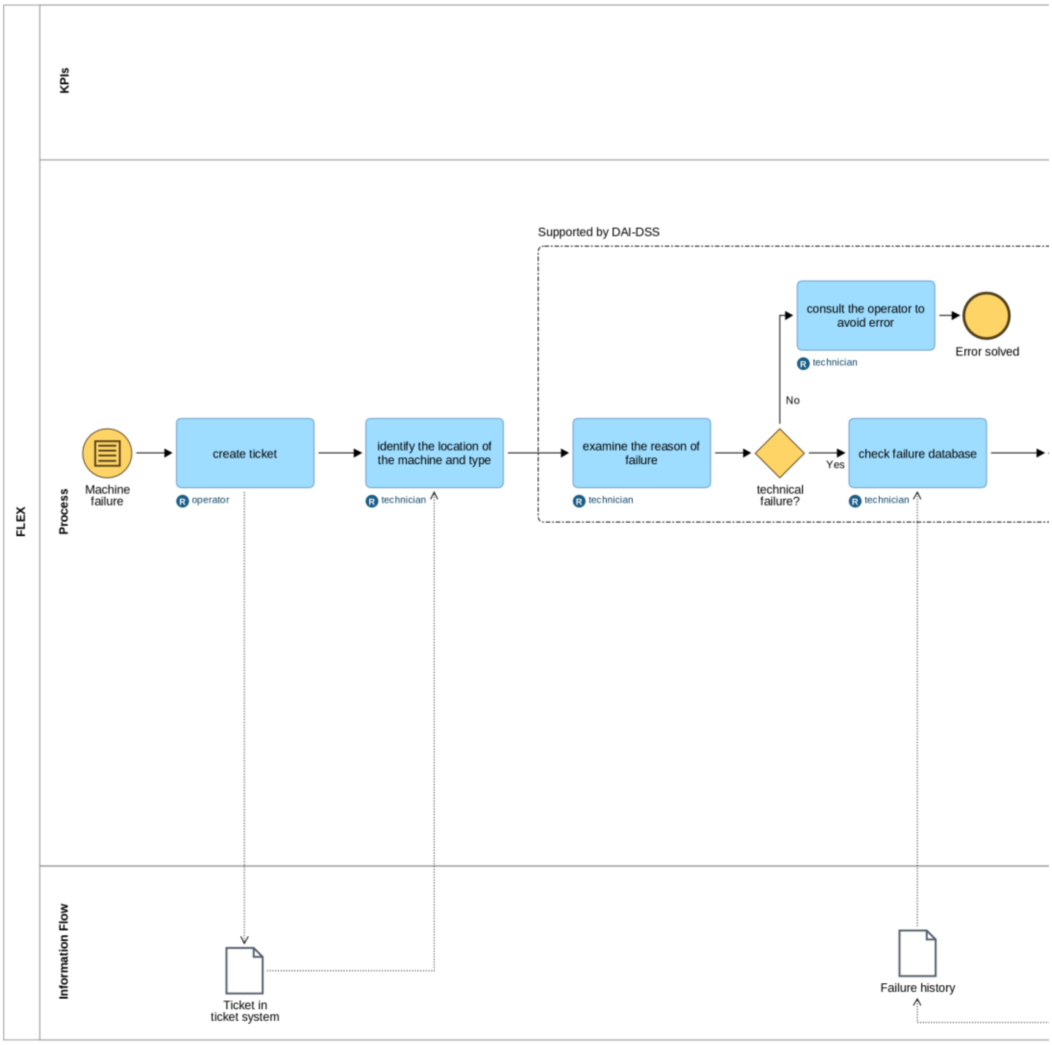

Figure 11: FLEX Machine Maintenance After Breakdown Process, part 1 (full size images at Annex A.7)

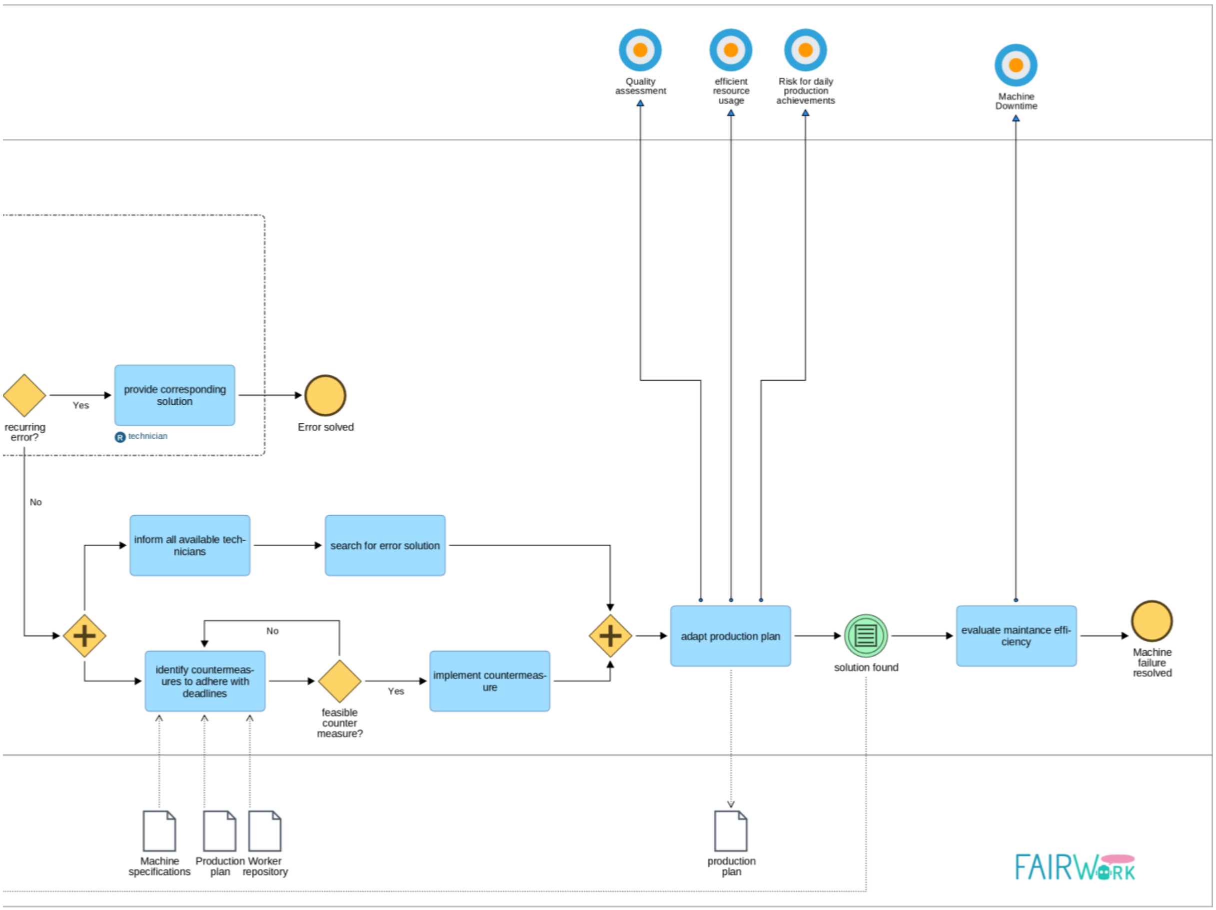

Figure 12: FLEX Machine Maintenance After Breakdown Process, part 1 (full size images at Annex A.8)

The process of scenario 3, about any maintenance activities after a machine breakdown and corresponding counter measures can be seen in Figure 11. It is triggered as soon as an error occurs, and the machine stops working. The first activity is to create a ticket in the ticket system, so that a technician gets a notification that his help is needed. The technician needs to identify the type of machine affected, and its location. Then the reason of failure is examined; in case it was an operator error it is solved easily through consulting, otherwise the failure database has to be checked whether it is a known error or not. In case it is known, the corresponding solution is provided in the error history too. If it is a new type of error, it is assumed to take longer to be resolved and all available technicians need to be informed in order to find a solution as soon as possible. While the technicians try to solve the problem, countermeasures have to be identified and implemented through rescheduling to other machines and reallocating the workers while considering the production plan. The new production plan must provide efficient resource usage, enable the production of same quality products and fulfil the orders within the deadlines. As soon as the new solution for the error is found, it is added to the failure record. The last step is to evaluate the maintenance efficiency and to consider the duration of the machine downtime.

2.3 Application Scenarios and Use Cases at CRF

This application user scenarios focus on decision support at the intermediate area between two specific production processes, which can be observed across the whole product life cycle, from design, to use as well as from raw material, to the assembled car, including all supply chains. Hence the potential to optimize and raise flexibility is extremely wide.

Each production line receives as input the products of the blanking lines: packs of metal sheets that are positioned by a worker and prepared to be inserted into the stamping process (Figure **13**).

Figure 13: Feeding the Pressing line with metal sheets (Stellantis data)

Stamping lines are made up of a succession of dies, each with a specific task. The first press is responsible for drawing, the process by which the sheet of metal is first shaped. Trimming, carried out by several presses, is intended to eliminate superfluous parts of the sheet. The settling press is responsible for molding the part as designed. Flanging gives shape to the secondary components, which are then used in the process of joining the various parts to the car structure. Finally, the drilling press applies the holes required by the design for future assembly or for aesthetic reasons. Figure 14 shows a series of dies outside the production line, in one of the dies warehouses.

Figure 14: Series of dies outside production line (Stellantis data)

In our use case we focus on the intermediate areas between the automotive press shop and the automotive body shop. The press shop gets the raw material delivered and very heavy punching machines (several tones strong) arranged in up to 15 parallel lines to create body parts. At the end of the line, 2 to 8 persons handle, quality check, and ship heavy, sharp, and unhandy parts from the line and place them on autonomous vehicle to carry the parts to the warehouse of the succeeding body shop.

When the products come out from the last die, they are ready to be put into their respective containers. The stevedoring workforce at the end of lines is responsible for this. The allocation of workers at the end of the line is done according to precise ergonomic rules: depending on the weight and size of the product design and the speed of the production line, one or more people may be needed to place the parts in the containers. Once filled, the forklifts take care of placing the containers on the train of racks waiting in the designated space in front of each production line (Figure **15**).

Figure 15: Forklift responsible of filling racks (Stellantis data)

Workers cooperate with robot arms and vision systems to handle, verify, and place components onto the transport device, which is either an autonomous vehicle or a human-driven forklift. Cost, time, quality approval and quality of transport are current major concerns, with a central focus on worker safety in cooperation. When operating conditions vary (e.g. for quality issues, material or resources availability, increase of demand, requests, or other constraints from the body shop), the press shop must accommodate with this new context, assess the situation and re-schedule production immediately. These events may happen several times per day and require real-time action. Current decision making tends to quickly solve the problem and find an ad-hoc compromise in a local optimum. As decisions to (re-)allocate the workload between human workers and robots, decision on work-speed, allocation of dangerous or high-quality tasks to human workers or robots have to be performed several times per day, per line, per intersection, the effects of all such decisions sum up to significant factors of the overall system.

To derive the various use cases from this complex production environment different approaches were used. Figure **16** introduces the three use cases at CRF as the three columns: (a) Workload Balance, (b) Delay of material, (c) Quality issues.

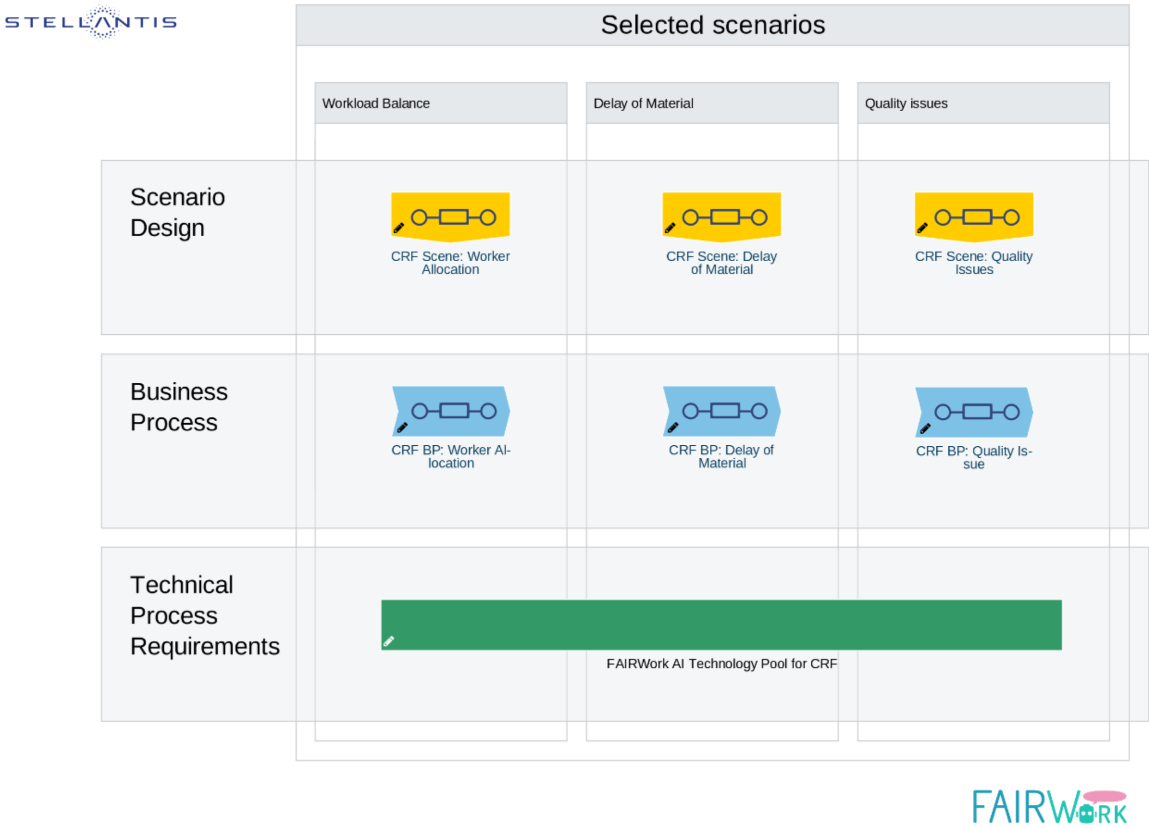

Figure 16: Alignment of Scenario Design wit AI technology for CRF

In the so-called “scenario design” layer, design thinking was used to describe the production system in form of a storyboard. From this overview scene, more concrete processes have been modelled. For each scenario one process model was created and they a located in the “Process” layer.

The third layer depicts the range of AI technologies that are accessible and that can be utilized to help with the difficulties outlined in the various scenarios and processes. While the same AI Pool is accessible in all scenarios, not all AI technologies are applied in all use cases. A modular approach should allow for the mapping of appropriate AI services to various types of decision challenges.

2.3.1 Creating Scenario Design using Design Thinking

During an onsite visit at CRF a design thinking workshop was done to get a better understanding of the complex production environment and the use case scenarios. The result of the workshop was the scenes shown in Figure **17**, Figure 18 and Figure 19. Based on several follow up meetings three use case scenarios could be derived from the scene:

a) workload balance,

b) delay of material, and

c) quality issues.

The following sections describe each scenario in more detail.

Scenario 1: Workload Balance

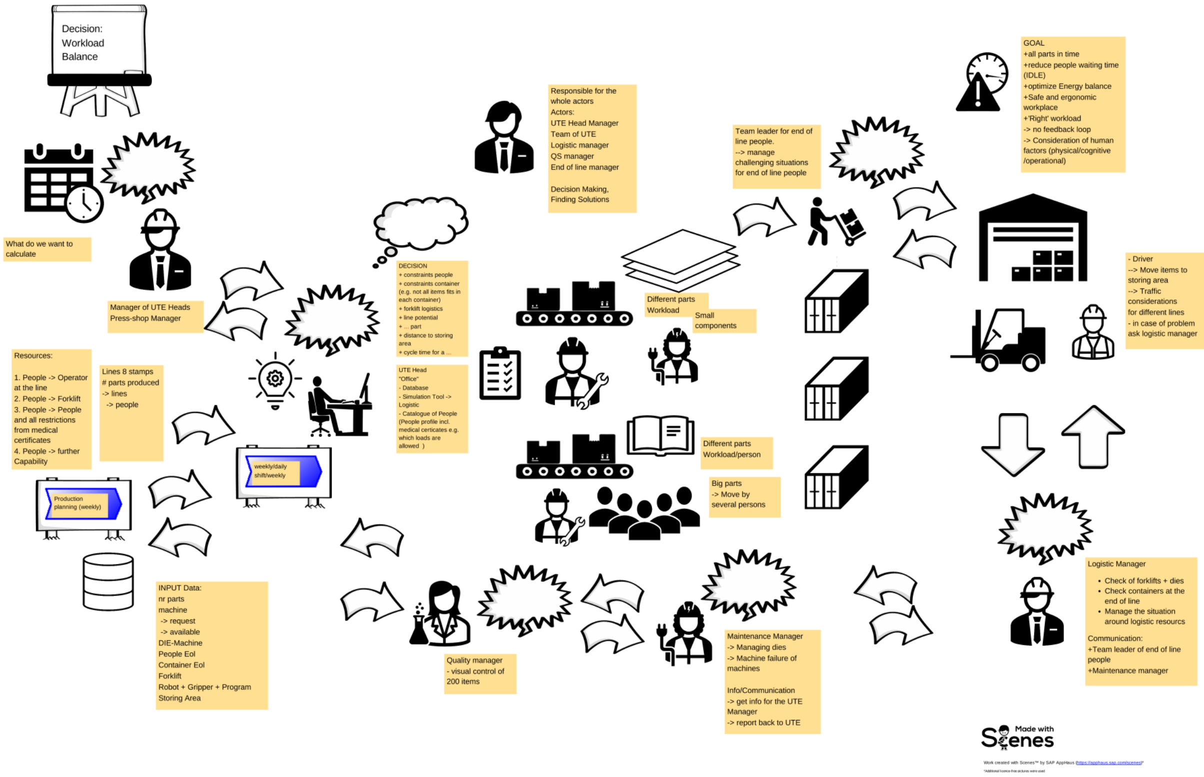

Figure 17: Scene CRF Workload Balance (full size image at Annex A.10)[6]

The use case concerns an UTE (e.g translated in Elementary Technological Unit), which can consists of a varying amount of stamping/molding lines. Each stamping/molding line is managed by a machine head, that responds to the UTE head. Production planning for these units is done on a weekly basis and there is input data coming from the press shop manager that can influence the production plan for the unit. This input data includes the number of parts that need to be produced, how many machines are requested and available, logistic information regarding containers, forklifts and the storing area, which robots, grippers and program is needed, and how many people are involved in the production process. People are very important for the whole production, as they play different roles throughout the process (e.g. operators of the line, forklift drivers, unloading personnel at the end of line, etc.). The UTE head takes all these factors into account, when planning the weekly and daily production for the unit. The responsible needs to adjust the production plan on a daily basis, when unexpected events (e.g. quality issues, event of sickness, urgent orders) influencing the production process, occur.

The UTE heads planning task includes giving each machine head the information about the daily target amount of components that need to be produced. Such components can vary in their geometries. Thus during the day, when the geometry to be produced changes, it is necessary to rearrange the line. This is done by replacing the molds of the presses (they are mounted on removable trolleys) and by replacing the grippers for gripping the semi-finished products between the presses.

Depending on the shape and weight of the produced components, different amounts of unloading personnel called “stevedores” is needed. The UTE head needs to assign the right amount of people to each end of line, taking also medical restriction into account, as not every worker can lift the same amount of weight. When planning the

[6] Work created with Scenes™ by SAP AppHaus (https://apphaus.sap.com/scenes) and licence-free images

production the UTE head has to check a database with a catalogue of peoples profile including their medical certificates to know which loads are allowed.

At the exit of the last press the stevedores take the component from a conveyor belt, checks it visually and, if good, deposits it in racks. The racks are handled by the forklift drivers. They pick up the full racks, deliver them to the storing area and bring back the empty ones. As the racks at the end of the line are limited and the lines stops if there are no free racks available, logistic must be working fast and efficient. Forklifts have a certain capacity and they are working on battery and need to be charged from time to time. These aspects may also be relevant for the whole process. The forklift drivers respond to the logistic manager, who manages the situation around the logistic resources (e.g. the volume of the warehouse, assigns tasks to the drivers) to ensure punctual and continuous availability of them.

As production lines are producing different components during the day and this leads to changes in the lines and to the number of required people, the reallocation of workers is a recurring process. Changing production lines can influence logistics as well, as paths from the lines to the warehouses are changing and components differ in size and weight, which influences how many parts can be transported and stored.

Besides, from producing all parts in time the goal of this use case scenario is to balance the workload for the different people involved in the production process to ensure a safe and ergonomic workplace. For doing so, human factors (physical, operational, and cognitive) have to be taken into account. Meeting medical restrictions is one thing, but in addition workload should be evenly distributed, so that not one person ends up doing the heavy work over and over again. Establishing a feedback loop could be beneficial for checking if workers feel treated in a fair way.

Scenario 2: Delay of material

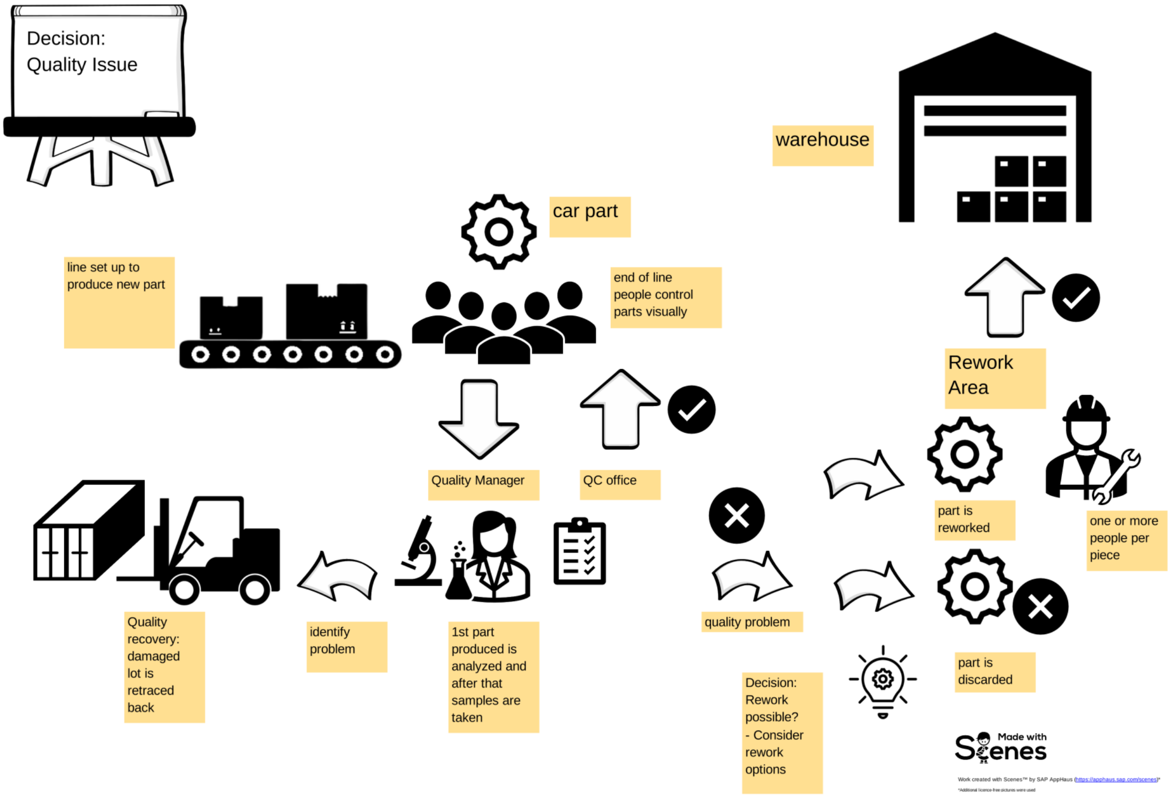

Figure 18: Scene CRF Quality issues (full size image at Annex A.15)[7]

In this scenario, procurement or logistic problems should be considered. If sufficient raw materials are available on the markets, warehouse optimization strategies could be followed to minimize delays of material through predicting the needed amount for the accepted orders. The prediction of demand would solve material shortage in advance. However, if sufficient material is available in general, the main challenge is to solve internal logistic problems, so that the needed materials and containers for storing the finished products are on time at the correct lines and plants, to minimize the downtime of each line. In this case the material must be delivered before production and thus the coordination effort takes place in the pre-production phase. A decision support system should define how the material and containers must be optimally allocated to minimize the downtime of the line, and to create the possibility to re-allocate the workers as well as the order scheduling to prevents potential downtimes.

Based on the product requirements, the orders are allocated to lines, each line is composed of a fixed number of presses, but not all orders need to go through all steps. Allocation of the orders should be in such a way that no line is threatened with downtime due to material or container delays of internal logistic failures. The process starts with the pre-production phase which is defined by incoming order allocation and their features like quantity, type of product such as finished, semi-finished products, and customer details. Before allocation to the production lines the required type of raw materials and their amount must be identified. Then the warehouse must be checked to see if the needed materials are available and a logistic manager must plan each line's supply with the necessary raw materials. The UTE head is responsible for assigning the tasks for producing the orders to the machine head who is then responsible for one specific line's production. Before assigning the orders to the machine heads, the UTE head should consider the optimal allocation of orders to the lines to minimize the overall downtime. Therefore,

[7] Work created with Scenes™ by SAP AppHaus (https://apphaus.sap.com/scenes) and licence-free images

the UTE head must take several constraints into account to achieve the objective. First, he must check if enough raw material of a certain type for one order is available, else when the raw material needed will be available for production. Is also important to evaluate how long it takes to produce one order on a line within the delivery deadline or according to their priority. Furthermore, containers in which the finalized products are stored and shipped to the customers must be available and of the correct type and quantity so that the products can be put from the line into the containers. To minimize the downtime, the lines should run and produce orders without interruption, therefore all assigned orders need to have their corresponding raw material and container supply as soon as the order starts to be produced. Also, only one order after another goes into production and each order should be produced at one line. In terms of logistic effort, it is beneficial if orders with a similar need for materials are produced at one line so that paths from the warehouse to the line stay the same. However, this is only valid if enough material is stored at the warehouse and there is no need to switch to a backup line. If there is not enough material due to market shortages, the utilization of material should be in such a way that the maximum number of orders can be produced.

Scenario 3: Quality Issues

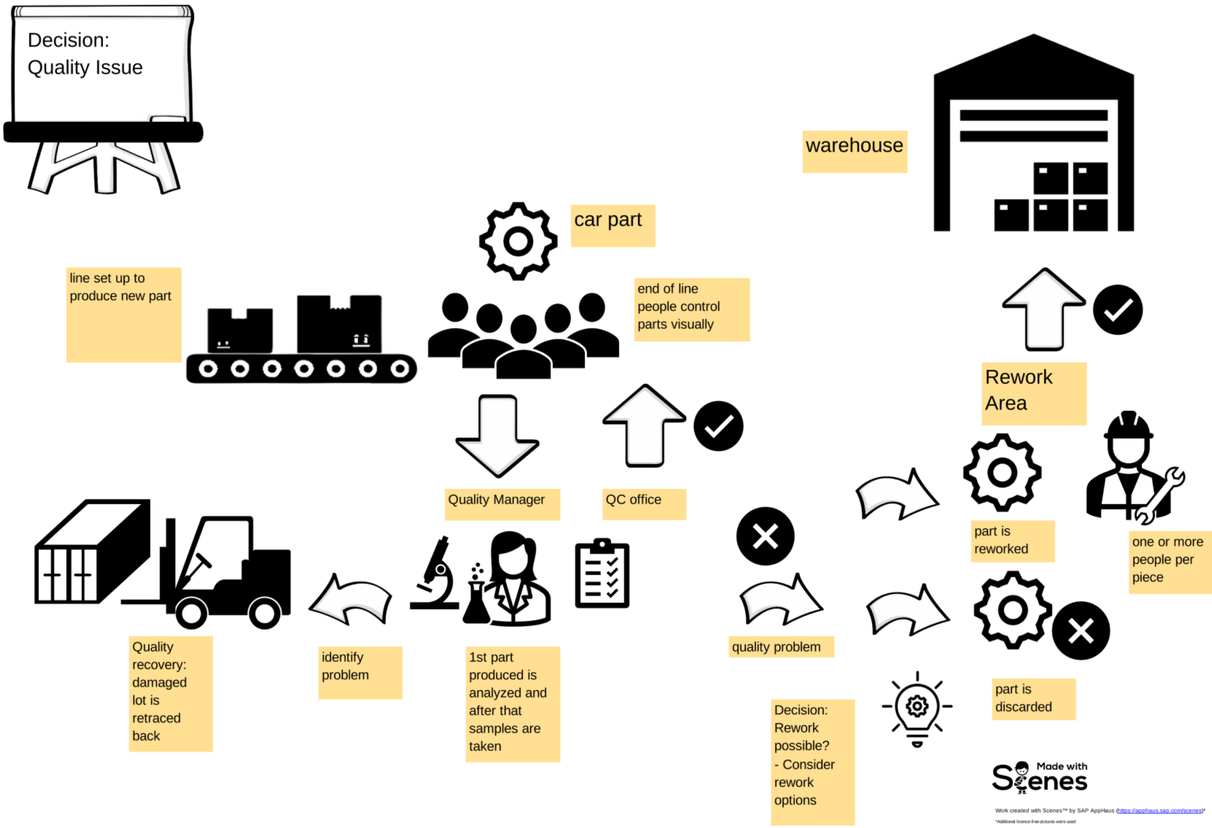

Figure 19: Scene CRF Quality issues (full size image at Annex A.15)[8]

When a line is set up to produce a new geometry, the first moulded products are checked in the metrological rooms, called "Quality corners", to verify that everything meets the quality standards. If the outcome of the check is positive, production can be started at full capacity. During the production, the decision on the quality of parts is made by a preliminary analysis of surface defects by blue collars at the end of the line. Subsequently, the quality staff check the relevant parts by in "Quality Corners" at the end of the line.If quality problems are identified, the so-called "quality recovery" is carried out, i.e. the lot is retraced back until the first qualitatively good piece is identified. Products with bad quality, depending on the defect found, can be discarded or reworked. At the same time, they try to identify the problem that caused the quality drift. The "Quality Corner" is shown in Figure **20** below.

[8] Work created with Scenes™ by SAP AppHaus (https://apphaus.sap.com/scenes) and licence-free images

Figure 20: Quality corner (Stellantis data)

The rework area is a zone that is designed to receive parts that need further processing before they are sent to the warehouse. It contains a rework warehouse and rework stations. The additional work phase that the parts undergo here is very costly and time-consuming: in fact, each part that arrives at the rework area must be checked and processed individually by one or more workers. This phase exists because some parts need further processing to reach the quality standards required by the customers. In addition, die deterioration can cause cyclical defects in the produced parts that make them unsuitable for shipment. Therefore, there are predictable rework operations, for example on the external components of "premium cars". While there are other reworks that are not predictable and are determined at the time of production.

There is also a QC office, where defects are analysed based on material characteristics, with the aim of tracing the behaviour of the metal sheets as they pass through the stamping processes.

2.3.2 Detailing Application Scenarios with Processes

Within the CRF user scenarios, we studied several detailed application scenarios where complex decision making is a crucial part of the overall process. We have now worked out detailed complex decision scenarios where humans play a crucial role in the entire complex decision-making process.

We started with a high-level company map that provides an overview of the organization's relevant processes (Figure **21**). We customized the map to describe CRF's processes based on standard company maps for the industry sector. The processes that should be supported by the decision support system have then been identified.

In case of CRF these are the **Scheduling**, **Rescheduling Operator** and **Machine Allocation**.

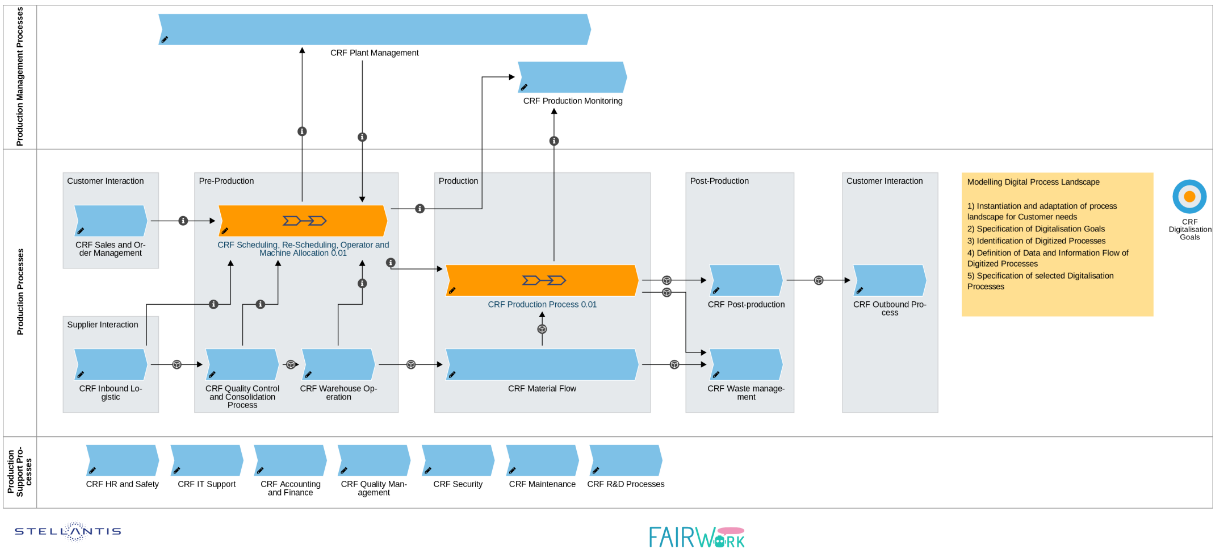

Figure 21: CRF Production Landscape (full size image at Annex A.9)

Now we zoom in on the processes and use BPMN to create process diagrams for each scenario. The Workload Balance is the first use case scenario we examine in more detail

Process Scenario 1: Workload Balance

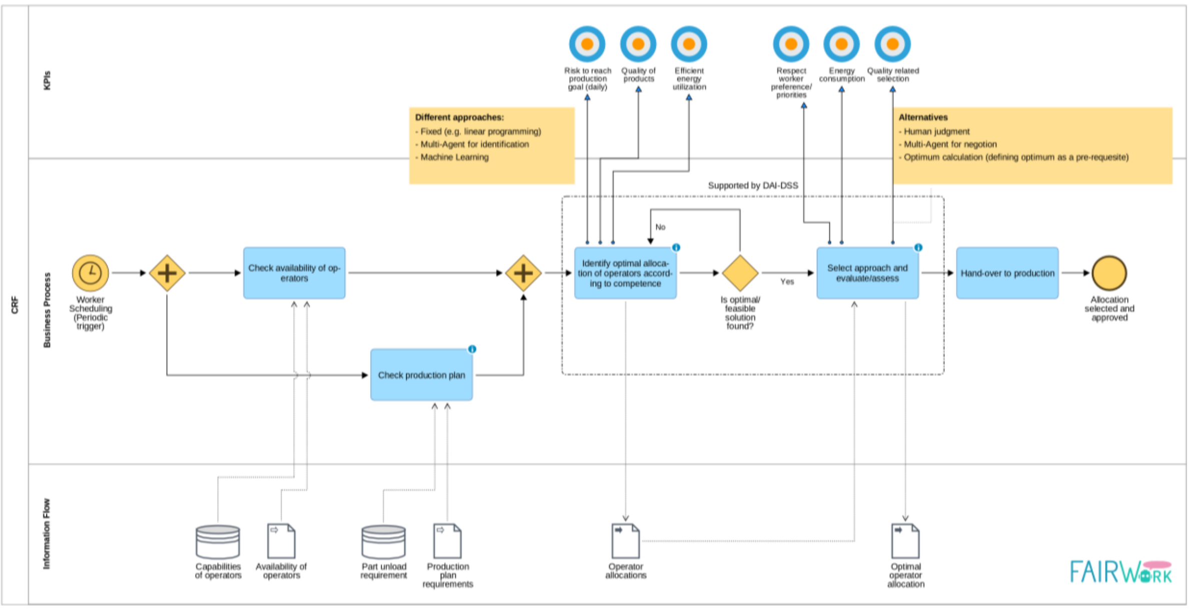

Figure 22: CRF Workload Balance Process Diagram (full size image at Annex A.11)

The process describes the scenario for finding a good workload balance in more detail than the scene. The process is triggered by an event which makes an allocation or reallocation of workers necessary (e.g. planning the weekly production, a change in the production lines etc.). The start event is followed by two parallel tasks, where one concerns availability of the operators and the other the production plan. The production plan specifies the production requirements (e.g. requested number of parts) and influences how many people are needed to fulfil all orders in time. Before assigning people to certain lines or positions, their availability and their capabilities need to be checked by accessing a database. Capabilities of operators include passed trainings, skills and medical conditions. After all input data is collected, the allocation of workers is done in two stages, where both stages should be supported by the decision support system. In the first stage, possible allocation scenarios are identified, considering the competence and availability of the workers. From all identified scenarios it needs to be checked which of them are feasible. Feasible scenarios should be able to reach the daily production goal, should respect product quality, and are realizable in terms of machine and resource capacities. Different AI approaches could support this phase (e.g. linear programming, multi agent system, machine learning). The feasible scenarios are then further evaluated according to certain KPIs (e.g. workers preferences, energy consumption, quality etc.) and compared with each other. The best fitting solution is chosen and may include minor adjustments to fit the workers' preferences and priorities, as this is the main goal in this use case scenario. If an optimal solution is found the result is hande over to production.

Process Scenario 2: Delay of Material

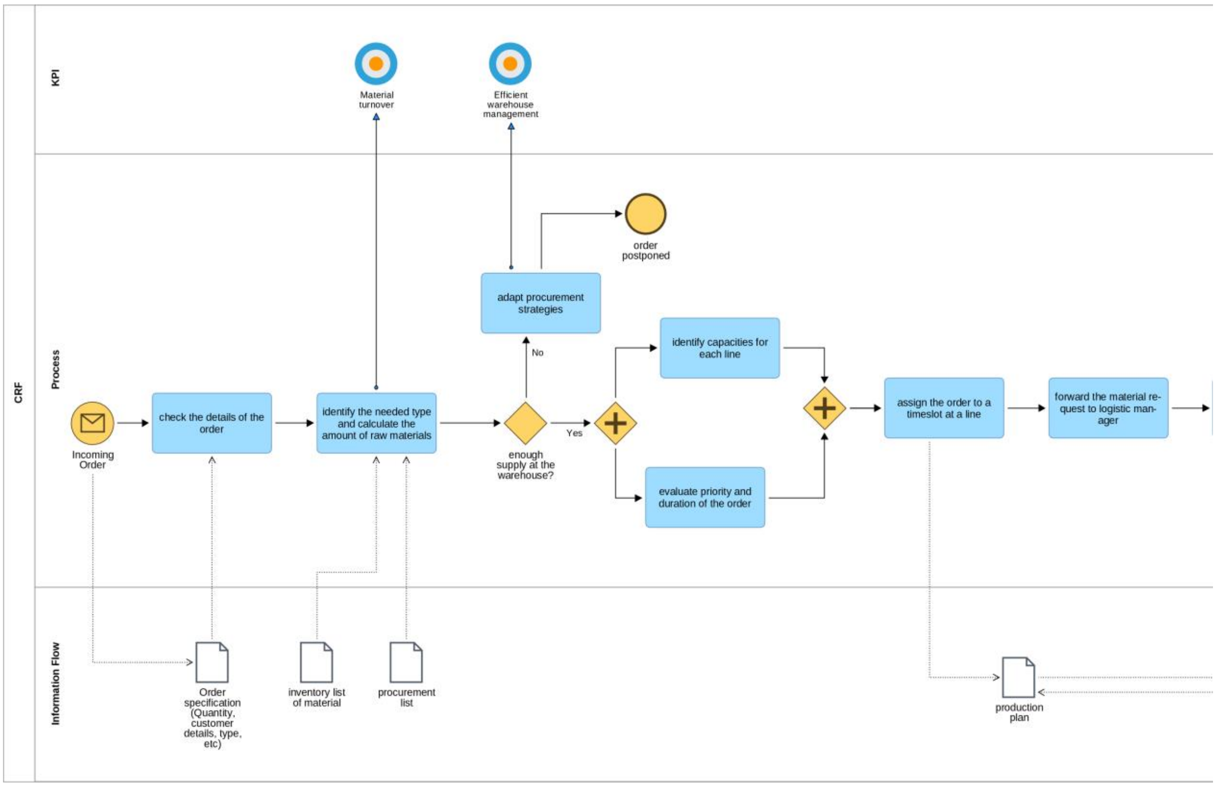

Figure 23: CRF Delay of Material Process, part 1 (full size images at Annex A.13)

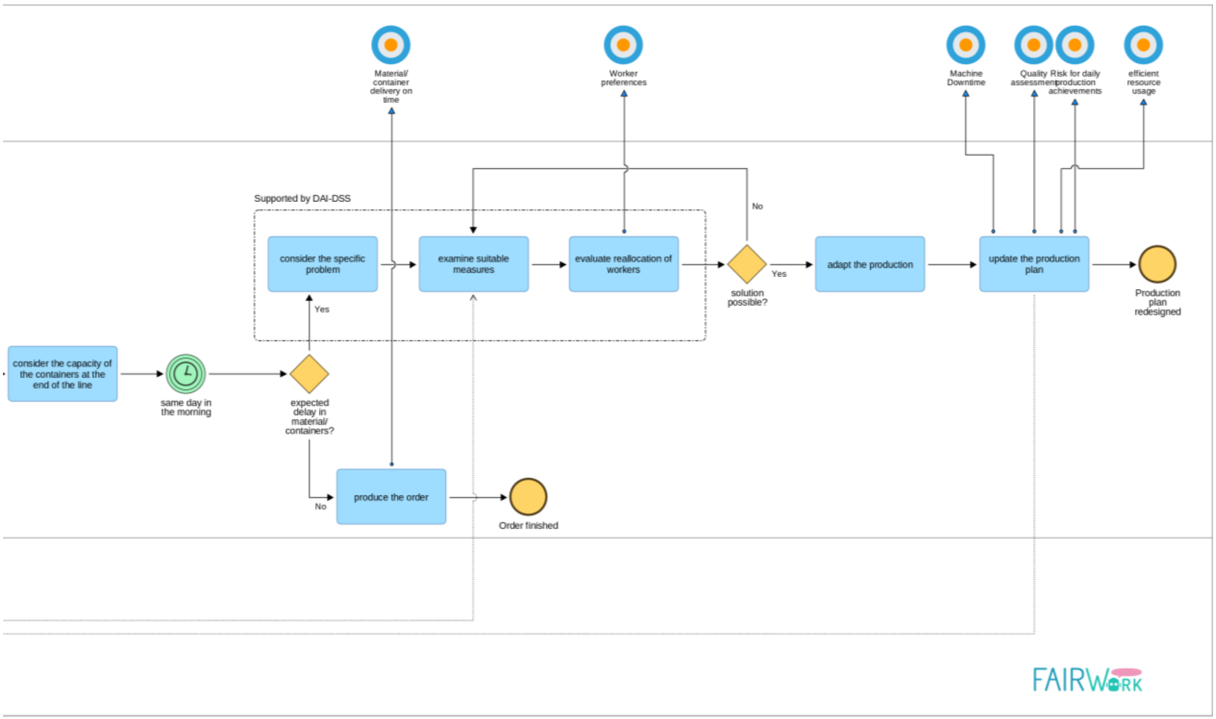

Figure 24: CRF Delay of Material Process, part 2 (full size images at Annex A.14)

The process of a delay of material delivery is illustrated in Figure 24 and starts with incoming orders with the corresponding order specifications. The first step is to identify the amount and type of the needed raw materials by using information about the level of inventory in the warehouse, as well as a procurement list in case material is not yet stored. In this step, material turnover rates might be calculated and used for information about material usage within the company. When there is not enough material stored at the warehouse, the procurement strategies must be adapted to these circumstances, as optimal warehouse management could prevent material shortages. If there is enough supply, identification of the line capacities and a ranking of the orders according to their priorities takes place. Also, the expected duration of one order is an important indicator for the allocation to the machines.

Then an optimal assignment to the specific lines takes place by the UTE head. The UTE head forwards the material request to the logistic manager, so that the material arrives at time at the defined line. Moreover, the capacity of the containers at the end of the line for storing the produced product must be considered. The logistics manager allocates the delivery tasks to its employees. In case a delay is expected, meaning that there is a lack of available containers, or the required material is not available, it is communicated in the morning on the same day of production. If this the case the UTE head must reconsider the production plan and identify adequate measures to avoid downtimes. These could be range from preparing the backup line, prepare similar containers for the product, postpone or stop the production in general. Also, an evaluation of reallocating workers while considering their preferences must take place. If the proposed solution is feasible, adaption of the production can take place, otherwise another solution has to be found. The last step is the update of the production plan regarding the changes. This activity includes an examination of the occurred downtimes of a line and the efficiency of resource usage. It is also important to assess the quality of the products that were produced at different lines due to rescheduling and to evaluate if the daily production goals were retained with the new production plan. When there is no expected delay of material or containers, the orders can be produced according to plan and the KPI “material delivery on time” can be derived which is an important indicator for efficient logistics of the company.

Process Scenario 3: Quality Issues

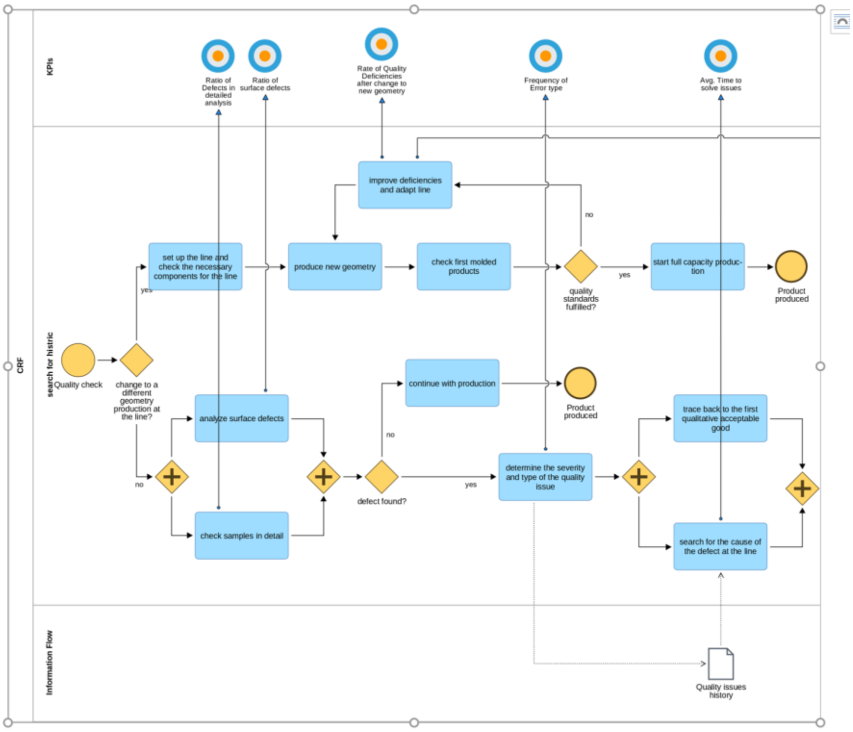

Figure 25: CRF Quality Issues Process, part 1 (full size images at Annex A.16)

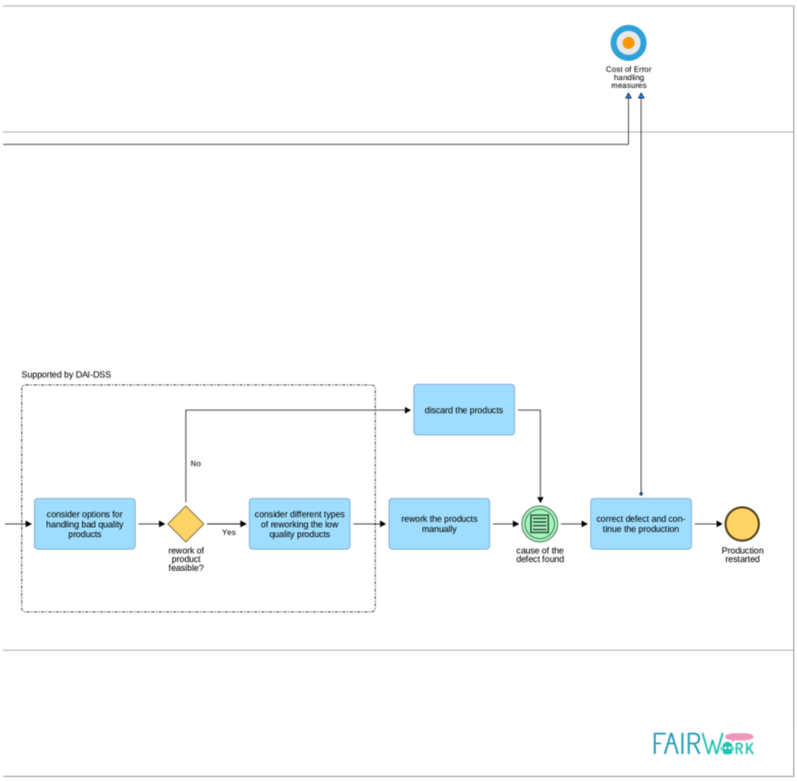

Figure 26: CRF BP Quality Issues, part 2 (full size images at Annex A.17)

The process of "quality issues" is a recurring process of quality checks and is illustrated in Figure **26**. It is either necessary for testing the quality of products that are produced after a line was set up for a new geometry and before production on full capacity or takes place during the ongoing production on a random sample basis. If a new geometry is produced the line must be set up and all necessary components for the line must be checked and prepared. The first molded products are then produced and checked for any quality issues. If the quality standards are fulfilled the product goes into full production. When the quality requirements are not met the deficiencies must be improved and the line must be adapted. Hence a rate of quality issues after changing to a new geometry and the cost for adapting lines can be derived. Then the new geometry product is produced again, which is followed by a quality check and should optimally result in a full capacity production start. When there is no new geometry produced, occasional quality checks through product samples take place. This check is performed on the one hand by blue collar workers directly at the lines by analyzing whether any surface defects can be seen and on the other hand by specialized quality management personnel who carry out detailed sample checks in the "Quality Corners". Within these activities, a ratio of surface defects and detailed sample defects can be provided. If there is no defect found, production is continued. If there are defects found, a categorization of the severity and type of defect is determined. In this step, frequencies of specific error types can be depicted. Then a traceback to the first qualitative inadequate good must occur while a search for the cause of the defect takes place. In the next step considerations about the handling of the inferior quality products are made. If the rework of the low-quality product is feasible, different ways of reworking the products are evaluated and then the products are reworked manually. If the rework not possible or feasible the products must be discarded. As soon as the cause of the deficiencies is identified, it can be corrected, and production can continue. The cost created for taking measures to handle the errors properly can be derived in a last step.

3 MODEL BASED ALIGNMENT OF SCENARIOS WITH DATA AND AI SOLUTIONS

In chapter 3, we give an **overview about the key challenges** of FAIRWork. In the current production industry there is a need to make current automated and hierarchical structured production processes more flexible. At the same time digitalization with AI support is seen as a key enabler for more energy efficient and resource efficient services, products or business models, by also enabling process optimization in the overall production process. Therefore, we describe in more detail the main technical challenges such as resource mapping and configuration, resource allocation, and resource selection aspects. These three challenges are highly relevant for making the process more flexible, adaptive, and resource efficient by using the relevant AI-based decision strategies in our complex distributed decision-making. At the end, the trustworthy AI aspect is a further key challenge to get AI accepted by the involved humans and utilize its potential.

3.1 Introduction into Decision Making

To support the decision making, a decision support system should enable different tasks[9], like analysis, prediction, and decision. Depending on concrete decisions and the context, only a sub-set of the introduced tasks may be supported. For the DAI-DSS system we will focus on the analysis and decision task.

Analysis means that data is available for a concrete situation, which can be processed to support decisions. Here the data cannot be mapped 1-to-1 to a decision, but a pre-processing must be applied. This pre-processing can be done completely or in a supportive manner (the human is involved in the decision making) by a decision support system.

With decision as a task of a decision support system, we mean that the system can make a pre-selection of possible solutions. The possible solutions can be created by the analysis through the processing of data. However, to better support the responsible humans, a pre-selection can be made. This could be done by ordering the found solutions in a meaningful way. What exactly the meaningful way is depends heavily on the concrete case. For example, the pre-selection or ordering could be done based on the costs or time of processes.

Even though we are not focusing on the prediction task in this state of the project, prediction could be that not only data of the current situation is used in the decision-making process, but also data that is assumed for certain possibilities (aka predictions). Simulation would be one example on how predictions can be created.

3.2 The Model-Based Alignment

After describing the application scenarios via design thinking and process podels and after listing available AI approaches and their corresponding Microservices with an AI Service Registry, we now deal with the mapping of the requested features and the available offerings.

Figure 27 describes the model-based alignment and configuration of AI algorithms in order to address the use case specific need. The process model represents the process scenarios for each use case and the DAI-DSS AI enrichment has the catalogue of application services for decision making. To provide decision support for the process scenario's the AI services from the catalogue can be selected. The configuration configures data sources requirements for AI services, which are then used by the orchestrator and the user interface component. The data

[9] Turban, E., Sharda, R., & Delen, D. (2011). Decision Support And Business Intelligence Systems (9th Edition). Prentice Hall. http://archive.org/details/Decision-Support-And-Business-Intelligence-Systems_201808

required for the services is provided by the knowledge base. For each use case scenario an overview has been provided to show how DAI-DSS Architecture support decision making process

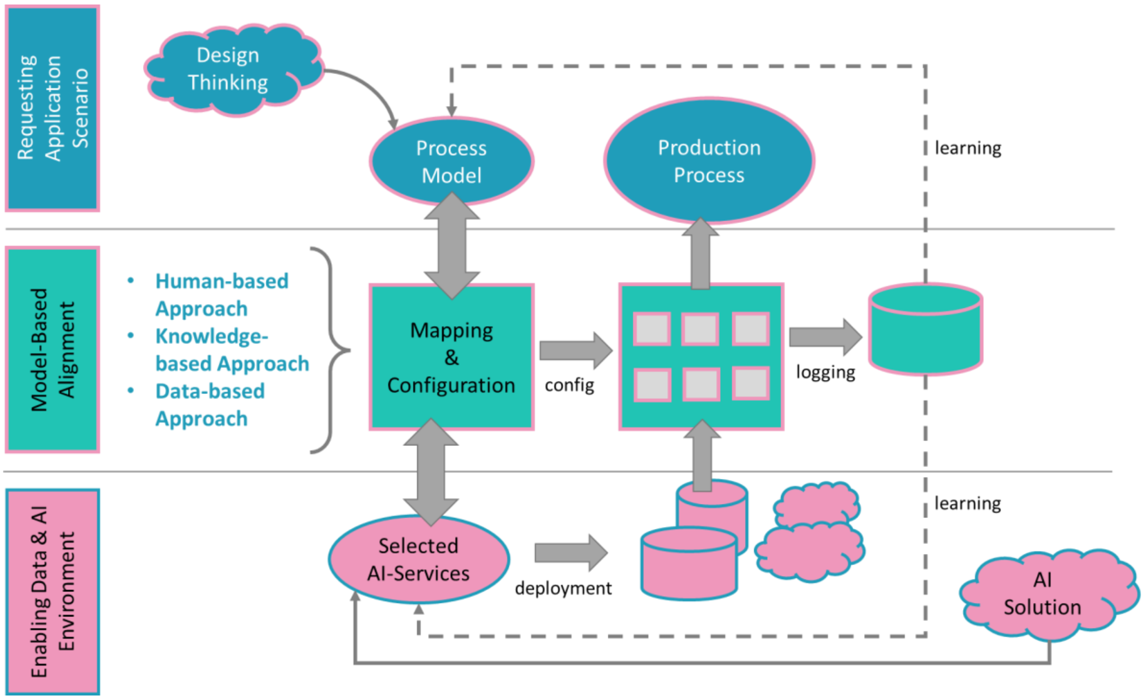

Figure 27: Model Based Alignment of Requests from Application Scenario with Enabling Data and AI Environment

3.3 Abstraction of Use Cases

In order to implement solutions that are helpful for the previously discussed use cases, but can also be adapted to the needs of other use cases (i.e. in the manufacturing domain), we abstracted the use cases and extracted three challenges: (a) the resource mapping challenge, (b) the solution configuration challenge, and (c) selection challenge. We propose therefor the AI solution for those generic challenges and hence not only provide solutions for the aforementioned use cases but also for a series of similar use cases challenges.

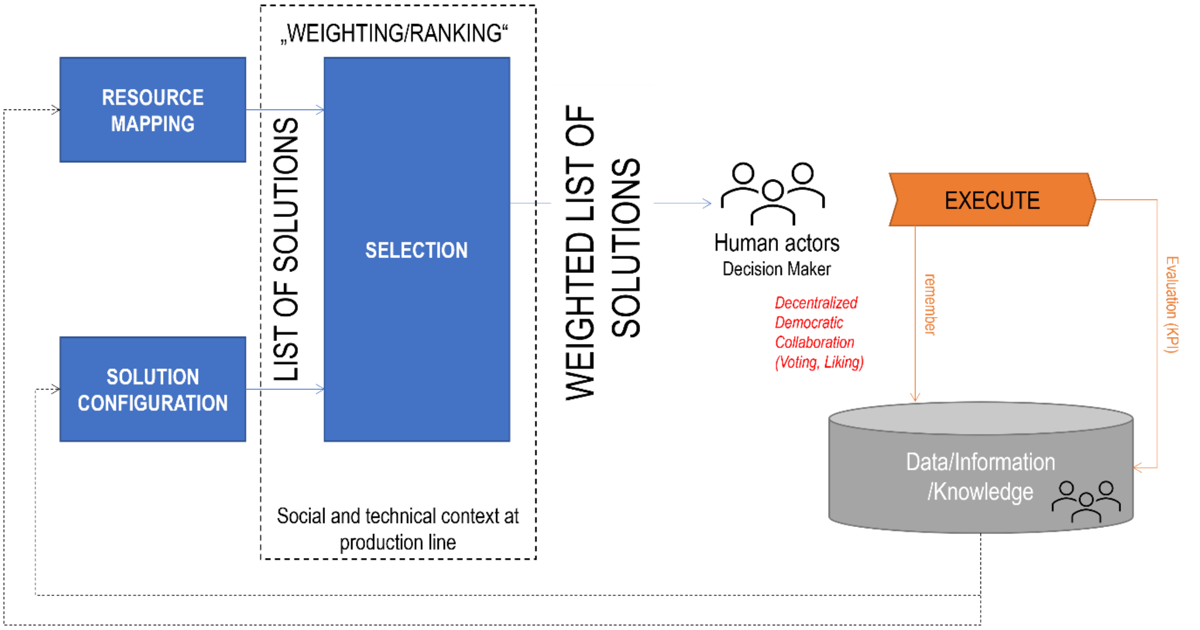

Figure 28: Abstraction of Decision Support Challenges and Their integration Into the Decision Support Process

Figure 28 shows the abstracted decision support challenges (blue boxes) and how they are integrated into the proposed decision support process. "Resource Mapping" and "Solution Configuration" are used for the Selection task, as introduced in the introduction of the chapter 3. They help by pre-processing available data and create solution candidates in the form of a list of possible solutions. Here "Resource Mapping" and "Solution Configuration" must not be completely automated tasks, but could needs further human input, to create the solution candidates.

The next identified challenge we call "Selection", which corresponds to the Decision task as introduced at the beginning of this chapter (section 0). Here the list of solutions is processed and ranked to create a pre-selection for the user. To allow such a ranking, the decision context must be available to the decision support system. Pre-selections can only be made by considering a specific goal, which is defined through the context. Therefore, the "Selection" transforms a set of all found solution in a list ordered/ranked based on the context of the specific problem.

This ranked list of solutions is then presented to human actors, who make the decision. Based on the concrete decision, the weighted list of solutions can be presented to a singular responsible human actor or to a group of human actors, who must make the decision together. Here a decision support system cannot only support the humans till the weighted list of solutions is created, but also by providing collaboration functionality for the human actors.

After the human actors have made the decision, the decision must be executed. The decision support system should save the human made decisions and evaluate them based on defined KPIs. This knowledge should then be used as input for future decision-making processes.

3.3.1 Decision Support for "Resource Mapping"

We identified these use cases as "Resource Mapping", where we can identify a requestor and a provider of some artefacts or services and where a matching between a requestor and a provider must be found. In our use cases we have machines that request operators with certain capabilities and operators that have certain capabilities. The decision support is in a mapping of available operators to the requesting machines. Here list of possible mappings will be created and therefore after "Resource Mapping" multiple solution candidates will be available, which can be further used in the introduced decision support process (Figure **28**).

Uses cases from chapter 2 which fit to the “Resource Mapping” decision support challenge:

FLEX:

- FLEX Worker Allocation

CRF:

- CRF Workload Balance

Although different use cases vary in detail and require different data and tool support, we abstracted this kind of decision in our “Resource Mapping” decision-support challenge, to create a more generic approach, with which more decisions can be described and supported. In the following section, we explain in more detail the identified challenges in “Resource Mapping” and list potential AI support.

AI technology can play different roles:

This decision support can be realized in form of a decision tree, where the human user or the decision support system (or both together) answer questions and are guided to a correct decision output. Depending on the complexity of the decision, the decision tree can be extended with semantics to allow a better mapping of the results or the decision tree can be made adaptive with rules, in order to not strictly follow the process but introduce a flexibility in the decision tree. Predictions with which questions the result set is reduced the most, can be integrated to reduce the number of questions which must be answered. Such decision trees are also often provided as questionnaires, which are answered by a group of experts. Such a crowd intelligence approach by combing decision trees, in different complexity with group based answers, can be used to tackle high complex questions. Cooperative answers can be weighted according to the relevance of the answer – e.g. experts get higher rates than juniors – to realize cooperative decision making.

Such symbolic AI based mapping requires that the request (of the requestor) and the offering (of the provider) are described in such a way, that the AI algorithm can interpret them. For example, the semantic description of a request is performed by the user, who selects from drop-down boxes or other forms of annotations, the correct description. In case the description is wrong, the correct solution will not be found. In complex scenarios, such semantic description can be so complex, that a thorough training is needed. This sometimes contradicts the aim to simplify solutions.

Therefore, sub-symbolic AI or data-driven AI using neural networks based on similarities can be used. Such networks interpret the request and identify the outcome. Once correctly trained, such networks have potential to interpret the request and find possible correct allocation with a high degree of correctness. However, a 100% correctness be established with such an approach because of its nature. Hence relevant allocation, or allocations with legal consequences cannot be performed in such a way. The allocation of a worker to a production line, in case a certain certificate is needed is hence not possible. However, the inclusion of worker preferences during allocation of production lines can be performed, as in most cases, the network allocates the correct production line.

A decentralized approach using agent-technology is also possible. In that way the agents try to find corresponding matchings between requests and offers. Worker or logistic agents would be configured in such a way that incoming requests are analysed and mapped to offers. In case offers should be mapped to a request (or vice versa) the corresponding agents can start negotiations to complete the allocation. There is a competition that the worker agent quickly gets allocated to avoid that other worker get allocated to the worker’s preferred machine.

In all aforementioned technologies the logging of decision is important, to learn and adjust the system. In case a network is biased or lead to wrong allocations of a certain request of a certain worker it needs to be retrained. In case agents are biased they need to be re-programmed as well.

3.3.2 Decision Support for “Solution Configuration”

With solution configuration we mean that there exists an adaptive system (e.g., a production line) and we want to adapt this system to fulfil a certain goal. To adapt the system, different parameters (e.g., order of machines) can be changed. A solution configuration is then variant of the system, which is defined by the values which are set for the available parameters.

Uses cases from chapter 2, which fits to the “Solution Configuration” decision support challenge:

<u>FLEX:</u>

- FLEX Automated Test Building
- FLEX Machine Maintenance After Breakdown

<u>CRF:</u>

- CRF Delay of Material
- CRF Quality Issue

For FLEX we identified these use cases as “Solution Configuration”, where in a limited set of possible configurations, the decision support system enables the finding of the configuration of these possible solutions. Use cases for “Solution Configuration” can vary in their set of possible solution configurations, as configuration challenges (like the configuration of automated tests) poses a more restricted solution spaces, compared to the case where these automated tests are not configured but implemented from scratch (here a greater set of possible solutions can be generated). Similarly, we identify the maintenance after machine break down as such configuration challenge, as e.g. the total re-implementation of the line is not an option, but the solution as to be found in a pre-defined set of possibilities.

For CRF we identified the uses cases for a reconfiguration of the production line in case of delayed materials and on the recognition of quality issues in the products. This decision support challenge was chosen because the it runs similar to production line. A production line is reconfigured for the new product, not rebuilt. Especially, as not only the production lines of products, for which the problems were recognised, must be reconfigured, but these problems can also influence the other products which are created in parallel.

Therefore, in “Solution Configuration” feasible patterns of solutions must be identified and prepared for the decision makers. Feasible patterns are those production line configurations which can be used in the situation, and which do not violate no-go criteria (e.g., a machine cannot be used at a higher utilization of its max. capacity).

In the following we explain in more detail the identified challenges in “Solution Configuration” and list potential AI support. To describe the “Solution Configuration” we need to define different possible “outcomes”. For simplicity reasons we explain the principle with three outcomes, (a) a limited and easy task, (b) an unlimited and highly complex task and (c) a task in between the two extremes. In reality, we will typically identify several alternatives from one or several outcome types. To explain the concept, we discuss the challenge with those hypothetical three outcomes. The three different outcomes also vary in how much human users are integrated in the finding of feasible solution configurations. These humans may or may not be equal to the humans who make the final decision, but the humans mentioned here can influence the created list of possible solutions.

AI technology can play different roles:

For a limited and easy task, the major input parameters and relevant configuration steps may be automatized in form of rules or workflows, where a sequence of questions or actions is performed and decisions or selections are performed either by the human developer or by AI with corresponding sensors. Corresponding sensors in hardware configuration may for instance be typical temperature or vibration sensors observing manufacturing machines, while in concept design, the term sensor may be taken a bit broader and cover also virtual indicators for estimation and simulation. Once a decision tree can be formulated, the decision tree can be automated either in form of a workflow or in form of several rules that are executed in a sequence. Semantic annotation can extend the capabilities by providing a set of different decision trees, from which the most relevant is selected, as well as semantic annotation of the decisions or selections to use semantic inference to either perform a selection or decision. Such AI technologies – decision tree and workflow, semantic annotation and inference, rule specification and execution – belong to the group of symbolic AI and hence can be pre-defined and automized to some degree. It can be used to partly perform action automatically or provide suggestions to a human user in form of a support system.

For a task in between the two extremes, the aforementioned technologies can be used, but it is expected that human interaction is required. The decision support process may help the user during the phases of the project, but the decisions and selections with each phase needs to be performed by the human. The decisions may automate part of the process – i.e. security relevant aspects are a candidate – but either the results needs approval by the human or several alternatives or unfinished templates are provided to the human developer for completion. Semantic annotation and inference can be provided to find similar solutions and propose results, which need approval by the human developer. This technology can be extended by neural networks, which find similar projects – according characteristics of the input or characteristics identified during the decision process.

For a unlimited and highly complex task, AI may less be used for automation but more for finding similar solutions or competent persons for support. Both can be realized using neural networks, where similar projects are presented, ideally to merge several green field configuration projects to reduce the long-term maintenance effort. Having a repository which also tracks the designer / developer, the neural network may also detect that a programmer recently developed a very similar use case – as significant lines of codes / designs are similar – and introduce the two developers each other. This can be used to arrange so-called “pair-programming”, a technique where an experienced programmer checks the final solution of a junior programmer and approves the solution.

The aforementioned interaction with knowledge bases – either with rules, workflows, semantic annotation, or neural networks – support the interaction between a human person and the knowledge base. To extend this interaction, a collaborative approach is proposed enabling not only to interact with the knowledge base but also with colleagues who are knowledgeable in this domain.

Domain experts can configure an agent with their preferences, e.g. being asked or not being asked for a particular project e.g. customer, technology, setup, project size, re-used code fragments, and the like. Once the developer interacts with the knowledge base, the agents are aware of what the user is aiming for and then can decide to interact with the developer and monitor the project, or avoid contact.

3.3.3 Decision Support for “Selection”

For this decision support challenge, no concrete uses cases from chapter 2 are mapped, as “Selection” is applied to the results of the other decision support challenges (see chapter 3.3.1 and 3.3.2). As input a set of possible solutions is consumed and the output is a ranked list of such solutions. This ranking can be seen as a pre-selection of the decision support system which is provided to the humans who make the final decision.

It would be possible that the decision support system just chooses the best solution for the human decision maker, but this is not the goal of this project, as it is important to include the human into the decision-making process. In some specific cases a sole choosing of the decision support system may be wanted, but in general the humans should be included in the decision-making process.

To achieve the pre-selection, context information for the decision is needed. This means that the goal, which the decision should achieve, must be known. For example, a configuration of the production line which leads to minimal cost, minimal execution time, or maximal worker satisfaction. The goal can be defined through a single variable (as in the examples before) or a combination of multiple ones. Further, the goal depends on the specific decision problem and must be defined accordingly.

Therefore, the decision support system for "Selection" decision support challenge must be able to calculate a value for each solution possibility and then rank them. This means that for each found solution, all the information must be available, to calculate the wanted value.

Part of the research work is the creation of detailed technical and algorithmic requirements taking into account the framework conditions required by the project in terms of e.g. human resources. In most cases, different approaches with very different abstractions are possible. However, the choice of the model for optimal resource selection and the time constraints have a relevant influence on the conceptual solvability of the resource optimisation problem, so that model building represents a central scientific contribution.

3.4 Research Direction for AI-Supported Decision-Making

Technical Perspective

Given that decision-making can be a highly complex task where humans are not able to receive and process all the information to reach an optimal conclusion, AI is one of the approaches that can support decision-making. The available models and algorithms are of different types and can be used for optimisation, simulation, prediction, and decision analysis. The results of such AI analysis can together, support decision makers. AI methods can also be used to analyze different decision alternatives and predict their impact on production or business performance indicators.

The research area of the implementation of AI in the DSS is wide-ranging and therefore the first exploration steps focus on AI-supported decision-making at the process level as well as at the manufacturing operation (e.g. job shop planning) and control level. The initial research aims to provide a comprehensive overview of the current state of the art and thus identify research gaps.

Research questions are:

- How can the decision-making process in the manufacturing environment be accelerated through the use of AI methodologies?
- Which AI methodologies have been used in decision supporting systems in the manufacturing environment?
- How existing AI methodologies can enrich classical (e.g. rule-based) decision support systems in order to be applied in complex manufacturing processes?
- How do different optimization metrics or constraints affect a schedule in a manufacturing context?
- How and to what extent can AI techniques for optimisation be utilized in industrial scheduling?

Human Perspective

Human involvement in AI-supported decision-making has to be considered at numerous stages: When implementing rules or fuzzy rules, human knowledge needs to be abstracted. While this is a difficult task from a technological perspective, it is also a psychological question of how AI can be developed and implemented in a way that grants human acceptance and builds trust. In this regard, an important demand towards AI is transparency.

Flyverbom[10] emphasized that transparency is a “form of visibility management” (p. 110, 2016), Páez[11] requires transparent AI to go beyond technical explainability and provide understandability to the end users.

Transparency applies both when developing AI as well as when executing and using AI for decision support. Decision trees or rule based AI are often interpretable by humans and can thus (easier) be displayed in an understandable manner. Nevertheless, studies will shed light on how their processes are set up and communicated in a way to support human acceptance. However, neural networks build black boxes that are neither interpretable for developers nor understandable for end users. The challenge is to develop explainable models – most likely in form of post-hoc explanations – that allow for insight into the black boxes. Such insight is important on the one hand for developers to be able to improve the system but also for end users. We will conduct studies about the difference of transparency required for the user groups to adapt the system to their needs.

Research question are:

- What does successful AI enriched decision making look like for the involved human stakeholders in the respective use cases?
- What type of transparency do the different stakeholders require for which type of AI and which use case?
- How does transparency differ for the different AI stakeholders and how can AI be designed to meet their requirements?
- How do different types of transparency foster trust and how can the system be improved to increase acceptance and trust in these specific domains?

The psychological studies will research the implementation of visibility and transparency in AI to grant the effective use and transfer of information. In FAIRWork, the goal of these studies is to use transparency as a means to increase acceptance and usage. First, qualitative analyses shed light on the perspective and requirements of different stakeholders by means of interviews. Based on these results, hypotheses about usage, the effects of transparent AI systems in specific use cases and beyond can be formulated. Second, quantitative studies compare different ways of transparency and their effects on usage, acceptance and trust in the system, but also subjective control, contentedness with the working processes and subjective autonomy. These quantitative studies combine use-case independent AI research (along, e.g., Werz[12]) and specific FAIRWork systems to be able to find answers for the systems at hand as well as more general solutions.

Practical perspective

The actions of actors cannot be understood from a subject perspective alone; rather, the socio-technical arrangement as the context of such actions plays a central role. Therefore, the second perspective in the FAIRWork project, which focuses on people and human-technology interaction, takes a close look at precisely such socio-technical arrangements. These are investigated as practices in order to be able to analyse the interrelationship between individual action and structural action pattern scheme. To directly address this tension, this is of particular importance in highly technical contexts, such as the production lines studied. Such a study can be done by looking at socio-technical interaction situations within socio-technical arrangements. The concept of socio-technical arrangement allows to study around meso/micro situations of social actors and technical actants, which is

[10] Flyverbom, M. (2016). Transparency: Mediation and the Management of Visibilities. International Journal of Communication, 10, 0.

[11] Páez, A. (2019). The Pragmatic Turn in Explainable Artificial Intelligence (XAI). Minds and Machines, 29(3), 441–459.

[12] Werz, J. M., Borowski, E., & Isenhardt, I. (2020). When imprecision improves advice: Disclosing algorithmic error probability to increase advice taking from algorithms. In C. Stephanidis & M. Antona (Eds.), HCI International 2020—Posters (pp. 504–511). Springer International Publishing.

determinant of a practice. Such arrangements operate in terms of a "structured and structuring structure" as described in Bourdieu[13] and Giddens[14]. This is first of all structured by the ensemble character, the relational orchestration of people as well as things, and embodies an institutional form. At the same time, however, it is not rigid; rather, it is obstinately appropriated by actors and thereby changed. Therefore, it makes sense to use an independent term for it because of its ensemble character. The concept of socio-technical arrangement allows to depict the elements (from single technical objects to a multitude of human actors) that are put together in a selected action situation to form an ensemble. Thus, it is the joining of structured elements to a more or less complex structure that constitutes the socio-technical arrangement. Therefore, we have to address the following questions with regard to this research direction:

- How are individual practices of decision-making constituted?
- What are boundary-conditions of practicing specific affordances related to AI – and what are the limits of such an approach?
- What is the influence of the socio-technical context in democratic decision making?

These questions will be answered empirically in two case studies, which will be conducted at the two industrial partners. These case studies will be conducted using the following empirical methods. On the one hand, the scenarios on which the respective work processes are based will be identified and mapped by means of a document analysis. Based on this, interviews with employees will be conducted on the basis of two or three exemplary scenarios in order to find out the relevant expectations and forms of work performance. Finally, the sociological-technical arrangement of the production lines will be examined through participant observation. In the context of a triangulation, the readings of the socio-technical interaction situation gained through the various empirical methods are brought into context and systematically evaluated. In this way, not only an empirically saturated analysis of practices is available. Rather, relevant factors for modelling the decision support tool can also be derived from this, mapped, and the most relevant factors for further use in the tool can be selected in a joint analysis with the other research and development partners.

[13] Bourdieu, Pierre (1982): Der Sozialraum und seine Transformationen. In: Die feine Unterschied – Kritik der gesellschaftlichen Urteilskraft. Frankfurt am Main: Suhrkamp, pp. 171–210

[14] Giddens, Anthony (1984): Die Konstitution der Gesellschaft. Grundzüge einer Theorie der Strukturierung, Frankfurt am Main: Campus

4 SELECTED KNOWLEDGE- MANAGEMENT AND ENGINEERING APPROACHES

In chapter 4, the **overall methodology of making complex decision-making is outlined**. Within this chapter, we describe the overall procedure for implementing complex decision-making processes. Therefore, this chapter gives an overview about relevant concepts for the research direction and implementation of such complex decision making by using AI services.

Therefore, we deal with the correct selection and configuration of the previously mentioned AI based decision making services. For this we follow the well-known plan, do, check, act methodology, to:

- first select and configure an AI algorithm,
- then let them execute in real world challenges,
- then check with the help of log-files if the AI performs well and
- finally act in form of changes in the configuration.

4.1 Plan Do Check Act Methodology

The Plan-Do-Check-Act (PDCA) cycle[15] is a well-known technique for implementing continuous improvement.

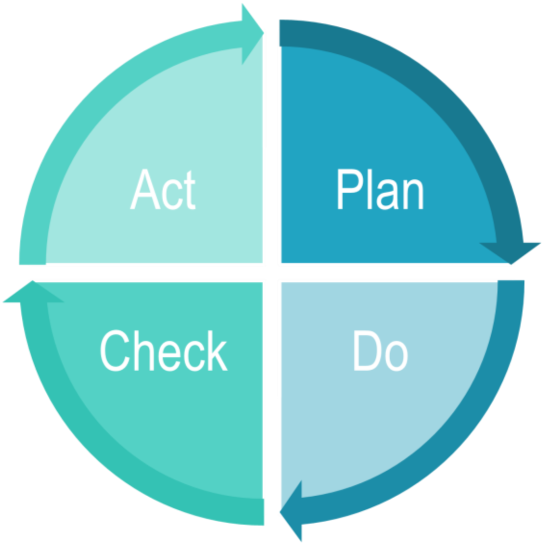

Figure 29: PDCA Methodology

The "Planning" phase consist of problem analysis, the creation of one or more solutions, and a strategy for implementation. The term "doing" refers to putting into practice the apparent best answer in light of the possibilities developed during the planning phase. "Checking" involves comparing the actual outcomes of implementing the selected solution to the intended outcomes. Finally, "acting" refers to examining and understanding discrepancies between results obtained and those anticipated, as well as coming up with novel solutions and strategies to avoid such discrepancies. At any level of an organization, PDCA is a broad technique that can be used to involve individuals or entire groups, for instance, during the design or manufacturing phases by Schmidt et al.[16]

This method can also be applied to define the AI usage for decision support, where the improvement of KPIs during the production and/or the design phase and a fair workload balance should be achieved by applying decentralized AI algorithms and services where needed. In the following the four phases in connection with the use case challenges are explained more in detail.

[15] https://en.wikipedia.org/wiki/PDCA

[16] Schmidt, M. T., Elezi, F., Tommelein, I. D., & Lindemann, U. (2014). Towards recursive plan-do-check-act cycles for continuous improvement. 2014 IEEE International Conference on Industrial Engineering and Engineering Management, 1486–1490. https://doi.org/10.1109/IEEM.2014.7058886

4.2 Plan Phase

The configuration environment provides tools and approaches for the planning phase in order to design how decisions in the use case are supported. In case of human actors, the configuration environment provides so-called semi-formal models, which are interpretable by human actors – often in form of graphical concept models – but not interpretable by artificial intelligence. In case the model is used for artificial intelligence, it must be well-formalized in order to enable interpretation by software programs.

We identified the following modelling approaches to configure the corresponding AI:

- **Process Modelling**
    - Models for human interpretation.
    - Typical process model notation can be used to define the criteria about a selection process. In case a "best fit" has to be found, there may be a sequence of decisions that shrink the search space in such a manner that the user – after answering a set of questions – found suggested relevant results.
- **Decision Model Notation**
    - Models for definition of rules.
    - Maybe it is possible to extend this notation to also cover Fuzzy Rule definitions
- **Semantic Representation**
    - We consider meta models as pre-defined semantic models. Hence, we propose domain-specific meta models that have the semantic integrated into their modelling languages.
    - Semantic models like taxonomies or ontologies, following a semantic web standard, are more flexible than the aforementioned pre-configured meta models.
- **Priority and Goal Models**
    - Currently there is no complete modelling languages to holistically define a multi agent approach. Rules and semantic inferences may be used to define the decisions in the header of an agent, Goal and KPI models may be used to define the aim of the agent and hence define the strategy or technical model can be used to support the complex configuration of a multi agent system. Although all those aspects are helpful in managing complex multi agent systems, there are still possible improvements to integrate the agent models into the domain specific use case environment.

4.3 Do Phase

After the configuration of the different technical components during the planning phase, the doing phase is concerned with the execution of the previously agreed plan. By looking closer at when decision making is needed for the use case scenarios we can observe that the decisions are either concerned with the allocation of resources e.g. the Workload Balance Scenario from CRF, or the implementation itself e.g. the Robot Programming Scenario from FLEX. So, if we look at it timewise, the decision phases are triggered by a new order or project coming in. This event is followed by an allocation phase, which in cases of limited resources can cause a triage. In the allocation phase is it necessary to clarify who takes on responsibility for the incoming task. This can be an individual or a whole team of employees. After the assignment is done, the realization of the order or project starts. In this phase multiple decision could be arise, where less or more support is needed depending for example on the experience of the person in charge. Different AI approaches are provided, to support the decision makers.

In FAIRWork, AI is used in all our scenarios to automate processes or to make their processes more resource-efficient. Since humans are an important part of the overall decision process, trust in AI and human factors plays an essential role, therefore these aspects are explained in detail. Finally, the technical concepts for a concrete implementation such as digital knowledge base, digital twin, digital shadow, will be discussed as well. Finally, it follows the explanation about the orchestration of decision-making processes by using micro-service.

4.3.1 AI for supporting Decision Making

Humans cannot always cope with evaluating complex and ill-structured decision-making problems. Such unstructured, highly data-loaded challenges often lack clarity and have no single best answer. This circumstance leaves potential for optimisation by supporting human skills with AI technologies. The aim to use AI in a decision-making process is to accelerate the speed and improve the accuracy as well as consistency of decision-making. AI also allows analysing big volume data, which is one of the most critical points in today's digitalised manufacturing and processes.

Decision-making with integrated AI can be defined as the decision-making process that is supported by various models or algorithms, which are developed based on available data. It is essential to be mentioned, that for the application of advanced AI solutions, large amounts of data, describing production and processes as well as their environment, are required. Decision-making consists of several stages, which can be seen in Figure **30** in Felsberger[17]. Considering the procedure outlined below, the third step - Model Development - is significant from AI technology perspective. The selection and development of a model is closely linked to the problem identification, available data, selected decision criteria, and global objectives. Furthermore, the created models should systematically produce different alternative solutions to the identified problems, in order to find the most suitable one or a set of recommendations to pick out.

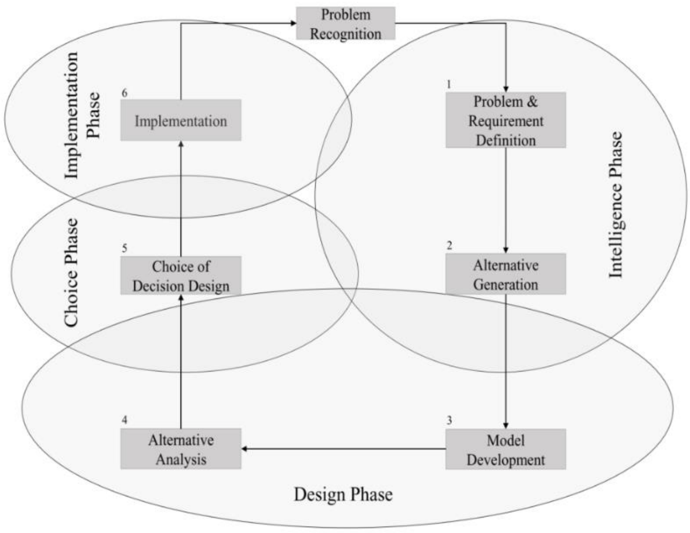

Figure 30: Decision-making process

There are various approaches to create a model or optimisation algorithm, but for our purposes, the knowledge-based decision support system (DSS) is the most suitable one. This approach has its origins in intelligent decision support systems (IDSS) from Nemati[18] and Negnevitsky[19]. That means that AI technologies are integrated in IDSS together with management expert systems, data mining and communication appliances. Currently, intelligent

[17] Felsberger, Andreas; Oberegger, Bernhard; Reiner, Gerald (2016): A Review of Decision Support Systems for Manufacturing Systems. In: SamI40 workshop at i-KNOW.

[18] Nemati, Hamid R.; Steiger, David M.; Iyer, Lakshmi S.; Herschel, Richard T. (2002): Knowledge warehouse: an architectural integration of knowledge management, decision support, artificial intelligence and data warehousing. In: Decision Support Systems 33 (2), S. 143–161.

[19] Negnevitsky, Michael (2005): Artificial intelligence: a guide to intelligent systems. Pearson Education.

systems for decision-making use neural networks[20], generic algorithms[21], decision trees or tables[22], fuzzy logics, as well as other accessible AI models or optimisation algorithms. Therefore, the knowledge-based DSS is designed to enable an identification of relevant knowledge using variety of data mining tools and AI technologies.

Rules, Decision Tree and Decision Table

Knowledge represented by a set of rules is simple to comprehend, quick to extract as well as to apply. Knowledge provided in the form of a decision tree or decision table can be used to create a number of rules out of it. Decision tables use rows and columns to store knowledge in a tabular format. A decision table, which consists of conditions and actions, provides a summary of the steps that are followed in response to various states of conditions, whereas a decision tree represents knowledge relationships in a hierarchical manner using nodes and links. A decision rule is a straightforward IF-THEN clause with a condition and a prediction. Predictions can be made using a single decision rule or a collection of numerous rules. Learning decision rule sets and lists can also be accomplished by using machine learning techniques as described by Molnar[23]. Decision trees and derived decision rules could be used in the allocation phase to map workers and machines or projects and available engineers.

Fuzzy rules

Fuzzy rules created on the basis of fuzzy logic can be used to map the preferences of people and machines. In this way, complex resource allocation issues can be solved. In such issues, job assignments to machines are often supported by internal knowledge provided by experts working daily in the productions.

Option 1: human preferences

The definition of preferences, in particular human behaviour, how one decides and what preferences one has, can be modelled with fuzzy rules. For example, if the human agent prefers collaborating with a specific robot at the assembly, he might classify his preference as follows: “I rather like Robot A and rather not like working with Robot B”. However, it could also depend on the temperature - if it is warm outside, one could have the following preference: "I would like to work in a hall where there is air conditioning, otherwise I don't care which hall I work in". According to this scheme, each agent is characterised by its drivers, which can be formulated in fuzzy rules.

Option 2: the general allocation workflow

Given the experience of human agents, their common knowledge and intuitive reasoning, the allocation of order to the machines performed through externalizing their knowledge within fuzzy rules.

Example: for ten years there has been a high share of an order that could not be properly produced with specific characteristics when human A worked with robot A in hall A. However, it was produced correctly when human A worked with robot A in hall B. The provided knowledge can even be used directly by decision-makers even without having any experience in this matter.

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[20] Kar, Arpan Kumar (2015): A hybrid group decision support system for supplier selection using analytic hierarchy process, fuzzy set theory and neural network. In: Journal of Computational Science 6, S. 23–33.

[21] Rabta, Boualem; Reiner, Gerald (2012): Batch sizes optimisation by means of queueing network decomposition and genetic algorithm. In: International Journal of Production Research, 50, 2720 - 2731.

[22] Shamim, A., Hussain, H., & Shaikh, M. U. (2010). A framework for generation of rules from decision tree and decision table. 2010 International Conference on Information and Emerging Technologies, 1–6. https://doi.org/10.1109/ICIET.2010.5625700

[23] Molnar, C. (2022). Interpretable Machine Learning (2. Aufl.). Independently published. https://christophm.github.io/interpretable-ml-book/rules.html

Even if only a vague formulation of rules exist, the fuzzy rules might indicate on which parameters the rules of producing the orders are based on. The fuzzy rules help reveal essential features of the decision-making processes of individual agents (esp. humans) or of the entire decision making process on how an order allocation takes place. This could be in a further step be incorporated into the overall system that considers all agents and their corresponding decisions making processes and underlying parameters.

Semantic

Projects or orders need to be described to categorize them according to their complexity and their characteristics. A textual project description can be easily interpreted by a human being, but for further interpretation by a machine this description has to be structured. The simplest way to do that is by using a form, where the project data needs to be inserted in a certain way. Another way to add semantics to a text is the use of annotations. This can be done by using an ontology or taxonomy to describe the characteristics of the incoming orders or projects. To create this ontology or taxonomy mutual characteristics for describing an order have to be found. When annotations are added to each description, they can later be found easily by applying a semantic search using the annotations as search parameters. Another reason annotations could be useful, is to categorize projects according to their complexity, so they support the assignment to workers or employees with suitable skills.

Artificial Neural Network (ANN)

Neural networks is used for forecasting and prediction based on historical data and as a class of quantitative models to be further applied in decision support systems. The ANN is used when the decision making process is complex with highly non-linear relationships between variables[24] where the decision tree or fuzzy logic are not capable anymore to handle all dependencies. One of the biggest advantages of ANNs over traditional systems is the ability to learn the underlying input-output relationships rather than following a set of rules specified by human experts[25]. Pragmatically speaking, ANNs are general function approximators that, in principle, can map any input-output relationship. Therefore, if an optimal input-output mapping exists for a specific use-case, it can be represented with an ANN. However, the development and training of ANNs require a great volume of data.

4.3.2 Trust in AI Decisions

Beyond technical questions, AI enrichment also entails the users' part. That means that the implementation of AI in this project also touches humans and thereby psychological questions. Despite the usage of AI in many contexts, AI augmented decision-making still faces barriers such as algorithm aversion (see Dietvorst[26]). This effect can prevent a successful implementation of AI in practice. Different studies have found ways to overcome algorithm aversion, e.g. when humans can modify the system discussed in Dietvorst[27], more when AI demonstrates its ability to learn[28]. However, the mentioned improvements depend on context and the existing technical features. A successful decision support-system has to match the algorithms and use cases with usage situations, individual requirements, and end users needs so that the AI system is accepted and used in the end.

What is more, when developing and implementing algorithms, i.e. AI, ethical aspects as described by AI HLEG[29] have to be considered. Important aspects are control and human autonomy, which have to be granted to all involved humans. In this regard, an important demand towards AI is transparency. Flyverbom[30] emphasized that transparency is a "form of visibility management" (p. 110), Páez[31] requires transparent AI to go beyond technical explainability and provide understandability to the end users. A successful transparency management that is understandable and sheds light on the AI black box should increase acceptance and usage of systems. At the same time, transparency is not a success by itself but bears the danger of what is known as "transparency paradox": "when there is an abundance of information available, it is often difficult to obtain useful, relevant information" and transparency can backfire, as shown in Stohl[32] (p. 134). We will conduct psychological studies about the implementation of visibility and transparency in AI to grant the effective use and transfer of information. In

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[24] Pechoucek, Michal; Riha, Ales; Vokrinek, Jiri; Marik, Vladimir; Prazma, Vojtech (2002): ExPlanTech: Applying multi-agent systems in production planning. In: International Journal of Production Research 40 (15), S. 3681–3692.

[25] Jain, A. K.; Mao, J.; Mohiuddin, K. M. (1996): Artificial Neural Networks: A Tutorial. In: IEEE Computer Society, Vol. 29, No. 3, pp. 31-44.

[26] Dietvorst, B. J., Simmons, J. P., & Massey, C. (2014). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114–126.

[27] Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. Management Science, 64(3), 1155–1170.

[28] Berger, B., Adam, M., Rühr, A., & Benlian, A. (2020). Watch Me Improve—Algorithm Aversion and Demonstrating the Ability to Learn. Business & Information Systems Engineering.

[29] AI HLEG. (2019). Ethics guidelines for trustworthy AI. European Commission. https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai

[30] Flyverbom, M. (2016). Transparency: Mediation and the Management of Visibilities. International Journal of Communication, 10, 0.

[31] Páez, A. (2019). The Pragmatic Turn in Explainable Artificial Intelligence (XAI). Minds and Machines, 29(3), 441–459.

[32] Stohl, C., Stohl, M., & Leonardi, P. M. (2016). Managing opacity: Information visibility and the paradox of transparency in the digital age. International Journal of Communication, 10, 0.

FAIRWork, the goal of these studies is to use transparency as a means to increase acceptance and usage. These psychological studies will both use use-case independent AI research along, e.g., Werz[33] and specific FAIRWork systems and run tests prior to implementation. This way we are able to find solutions both use-case specific and also solutions of more general nature. While these studies show ways to use transparency as a way to grant understandability, foster trust and thereby usage, another important variable of interest will be the perceived control, contentedness, and autonomy of those involved and touched by decisions. That is, despite the DAI-DSS being autonomous in its decision-making, humans have to have the final control over the system. This approach will investigate transparency as a means to overcome algorithm aversion.

The question of trust does not present itself solely as a question of individual trust in a situation, rather, the web of relations also plays a central role here. To what extent do the actors trust the structure in which they act and are ultimately embedded? We must ultimately keep two aspects in mind here. On the one hand, the literature on questions of infrastructure formation has made it clear that it is precisely the materiality of socio-technical arrangements that constitutes an important unit of analysis (e.g. Bowker/Star[34], Suchman[35]; Barlösius[36]). On the other hand, specific challenges in modelling such situations become apparent. This is because the targeted abstraction of socio-technical interaction situations and their modelling on the basis of a few factors necessarily inscribes selected boundary conditions into the model. These can provoke trust problems when they enter the real-world situation in the form of tools. This is because the selection and emphasis of these selected factors can then be perceived by the actors as too narrow and, in the worst case, even interpreted as an intended selection. In this respect, questions of trust actually arise in the implementation of such new tools as a socio-technical problem of the first degree e.g., Büscher./Sumpf[37].

Combining the two named approaches, we are able to identify solutions both use-case specific and also solutions of more general nature. While these studies show ways to use transparency as a way to grant understandability, foster trust and thereby usage, another important variable of interest will be the perceived control, contentedness, and autonomy of those involved and touched by decisions. The aligning view on the embeddedness of transparency as a structured context, shows whether ambitions of transparency and the structural realization of transparency are in conflict – or not. Transparent decision-making in complex socio-technical arrangements depends not only from individual capacities to take decision, but also from the structured capabilities. One principle in this direction is, that, despite the DAI-DSS being autonomous in its decision-making, humans have to have the final control over the system. This approach, as it offers a view on the whole picture of contextualized decision-making and the different forms of transparency therein, can also be seen as an investigation about transparency as a means to overcome algorithm aversion.

4.3.3 Human Factors in Decision-Making

Studies of human decision making have demonstrated that stress exacerbates risk taking. Since all decisions involve some element of risk, stress has critical impact on decision quality (Porcelli & Delgado, 2017[38]). Decisions are found to improve with stress up to an optimal threshold beyond which deterioration is observed. Naturalistic

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[33] Werz, J. M., Borowski, E., & Isenhardt, I. (2020). When imprecision improves advice: Disclosing algorithmic error probability to increase advice taking from algorithms. In C. Stephanidis & M. Antona (Eds.), HCI International 2020—Posters (pp. 504–511). Springer International Publishing
[34] Bowker, G.; Star, S.L. (2000): Sorting Things out. Classifications and its Consequences. Cambridge, MA / London: MIT Press.
[35] Suchmann, L. (2005): Affiliative Objects. In: Organization 12(3), pp. 379–399.
[36] Barlösius, E. (2019): Infrastrukturen als soziale Ordnungsdienste. Ein Beitrag zur Gesellschaftsdiagnose. Frankfurt am Main: Campus.
[37] Büscher, Chr.; Sumpf, P. (2015): "Trust" and "confidence" as socio-technical problems in the transformation of energy systems. In: Energy, Sustainability and Society 5, DOI 10.1186/s13705-015-0063-7
[38] Porcelli, A. J., & Delgado, M. R. (2017). Stress and Decision Making: Effects on Valuation, Learning, and Risk-taking. Current opinion in behavioral sciences, 14, 33–39. https://doi.org/10.1016/j.cobeha.2016.11.015

decision-making research (Klein, 2008[39]) shows that in situations with higher time pressure, higher stakes, or increased ambiguities, experts may use intuitive decision-making rather than structured approaches. They may follow a recognition primed decision that fits their experience, and arrive at a course of action without weighing alternatives.

Stress directly affects human decision-making (Galvan and Rahdar, 2013[40]): it can lead to a number of undesirable consequences, including a restriction or narrowing of attention, increased distraction, increases in reaction time and deficits in the person's working memory (Driskell et al., 1999[41]). Studies of human decision making demonstrate that stress exacerbates risk-taking and impacts decision quality. Since most managerial decisions involve some element of stress, decision aids such as decision support systems (DSS) have been proposed to mitigate its effects. Existing research has largely attended to two key stressors, time pressure and information overload. For a holistic understanding of decision making under stress and to improve decision support, an extended set of stressors and psychological experiences underlying stressful decisions is examined. In terms of a class of stressors called 'Decision Stressors' there are four Decision Stressors that affect decision quality: information overload, time pressure, complexity and uncertainty.

- Stress and Risk-Taking. Decision-makers' likelihood to engage in risk varies greatly based on multiple decision-inherent features including uncertainty, framing of a decision [as a potential gain or loss; 59], and valuations of outcome valence, magnitude, and probability of receipt. As such, decisions involving risk-taking rely in part on stress-susceptible valuation/learning processes.
- Information overload is "a gap between the volume of information and the tools we have to assimilate" it. Information used in decision-making is to reduce or eliminate the uncertainty. Excessive information affects problem processing and tasking, which affects decision-making. humans' decision making becomes inhibited because human brains can only hold a limited amount of information
- Decision fatigue is when a sizable amount of decision-making leads to a decline in decision-making skills. People who make decisions in an extended period of time begin to lose mental energy needed to analyse all possible solutions. Impulsive decision-making and decision avoidance are two possible paths that extend from decision fatigue. Impulse decisions are made more often when a person is tired of analysis situations or solutions; the solution they make is to act and not think.

Though many decisions must be made under stress and many decision situations elicit stress responses themselves (Starcke and Brand, 2012[42]), decision makers could enhance their decision-making performance and protect against potential decision failures (Whyte, 1991[43]) by means of adapting certain coping strategies, such as, follow:

- Use Balance sheet exercise. Janis (1982[44]) suggests that decision makers can foster vigilance by means of using the "balance sheet" exercise. This is a pre-decision process that asks the decision-maker to confront and answer the questions about the potential risks and gains not previously contemplated

[39] Klein, G. (2008). Naturalistic Decision Making. Human Factors, 50(3), 456–460. https://doi.org/10.1518/001872008X288385

[40] Galván, A., Rahdar, A. (2013). The neurobiological effects of stress on adolescent decision making, Neuroscience, Volume 249, 2013, Pages 223-231, ISSN 0306-4522, https://doi.org/10.1016/j.neuroscience.2012.09.074

[41] Driskell, James & Salas, Eduardo & Johnston, Joan. (1999). Does Stress Lead to a Loss of Team Perspective?. Group Dynamics: Theory, Research, and Practice. 3. 291-302. 10.1037/1089-2699.3.4.291.

[42] Starcke, K., Brand, M. (2012). Decision making under stress: A selective review, Neuroscience & Biobehavioral Reviews, Volume 36, Issue 4, 2012, Pages 1228-1248, ISSN 0149-7634, https://doi.org/10.1016/j.neubiorev.2012.02.003

[43] Whyte, G. (1991). Decision failures: why they occur and how to prevent them. The Executive, 5, 23-31.

[44] Janis, I.L. (1982). Groupthink, (2nd ed.), Houghton Mifflin, Boston.

- Use check lists. Kruglanski (1986[45]) suggests that potential decision failures could be prevented by means of a preparing a check-list for all aspects of the alternatives, and before selecting the "best" alternative, these aspects should be compared against to the criteria check-list.
- Heighten the fear of failure. Kruglanski (1986) advocates that inserting several reminders into the decision-making process may be help to raise the fear of failure. People may be assigned to remind the decision makers of the negative consequences of their course of action.
- Analyze the sources of decision-making stress. Several authors, such as Billings et al., (1980[46]) suggest that one of the significant sources of decision-making stress is the necessity of making a choice within a fixed time period. .Keeping the information load at a standard pace can have implications to reduce the level of cognitive and emotional stress felt by the decision-maker.
- Use decision support systems whenever feasible. It has been shown that decision support systems could be specifically designed to mitigate the negative effects of stress on human decision-making (Phillips-Wren and Adya, 2009[47]).
- Order task priorities. Research findings suggest that providing training on how to order task priorities and use efficient search strategies is an alternative way to enhance the decision quality and prevent potential decision failures while making decisions under stress. Several cognitive behavioural stress-coping training programs have been shown to be effective in combatting decision related stress (Cannon-Bowers and Salas, 1998). The main aim is to prevent panic in a stressful situation and to achieve the best possible cognitive processing and decision outcome.

FAIRWork will implement DSS to mitigate the negative effects of stress, applying AI-driven decision making. However, via human-factors-based analytics of the innovative decision making process, and considering the integration of stress-coping strategies above, we will lay a scientifically valid basis to design stress-reducing DSS for better, i.e., fair and more efficient decision making.

For the purpose of human factors based analytics for decision-making, the digital shadow of human operators requires a so-called “Intelligent Sensor Box” (ISB). The meaning of an ISB is to represent a human operator by means of a set of parameters that are pivotal for any higher-level decision-making regime. The digital shadow of the human operator ideally should be capable to quantify variables that characterise its physical, cognitive, affective, social and motivational behaviour, in interaction with its workplace environment. For this purpose, sensors would be attached within a body area sensor network via wearables, further sensors would apply surveillance tasks via remote measurement technology, and additional sensors would represent the workers’ context within the workplace environment via human-machine and human-environment interactions. These data would be transmitted as well to a globally accessible data lake that is related to the DAI-DSS Knowledge Base after having applied an anonymisation procedure. Within this Data Lake, global key performance indicators (KPIs) and functions are stored in order to be input to the AI-based enrichment module that will provide machine learning for further insight as well as optimisation methods both of which would enrich the global DAI-DSS environment.

4.3.4 Decision-Making using Workflows and/or Multi Agent Systems

Part of the planning phase includes the configuration of microservices. The idea is that multiple smaller services are combined and should interact with each other to solve a concrete use case. The result of this configuration phase should be a workbench, which enables the user to interact with the services during the “Do-phase”. Each workbench contains a set of so called “Widgets”. Widgets are responsible for the frontend UI and provide certain

[45] Kruglanski, A. W. (1986).Freeze-think and the Challenger, Psychology Today, August, 48-49.
[46] Billings, R. S., Milburn T.W. & Schaalman M.L. (1980). A model of crisis perception: A theoretical and empirical analysis, Administrative Science Quarterly, 25(2), 300-316.
[47] Phillips-Wren, G. & Adya, M. (2009). Risky Decisions and Decision Support - Does Stress Make a Difference?, Proceedings of JAIS Theory Development Workshop Sprouts: Working Papers on Information Systems, 9 (55). http://sprouts.aisnet.org/9-55

functionalities (e.g. semantic search, dashboard, list of similar projects, recommended link to read, list of persons to contact, access to Multi Agent System etc.). The way of interacting with these widgets and the communication between the microservices, can be done using different approaches and can be seen as different types of orchestration. The orchestrator component is in charge of this interaction task and we can distinguish three orchestration approaches: (a) human made orchestration by knowing where to click, (b) workflow orchestration, by combining different services and (c) agent based orchestration.

Orchestration by Human

One of the simplest ways to do orchestration is manually. The available widgets are displayed using a graphical user interface and the human interacts and triggers the services by clicking on them. The required inputs needed by the chosen widgets are provided by the user e.g. by uploading files, filling out forms, or choosing options from a list. Outputs resulting from the use of the widget are provided to the human user and can be used further if needed. In this case the microservice available to the user consists of a frontend and backend part and the data coming from the user is processed by the service itself without communicating with other microservices. This way is a good starting point for building a prototype, because it is easier to implement and configure individual services that are independent from each other. But this approach has its disadvantages regarding the user experience because outputs need to be adjusted manually to fit the following service inputs. Also, it misses the benefits regarding modularity and reusability, as each service is hardcoded and manages the frontend and backend components on its own. Parts of one service cannot be reused by other services.

Orchestration by Workflow Engine

Being able to combine different UI components with different backend services or different backend service with other backend services is a powerful feature that increases the usability of each UI component and the reusability of microservices. If the use of multiple microservices is needed, a workflow can be created by combining them. The workflow is defined in the configuration phase by determining which microservices are used and, if it includes also a front-end service, the result is a separate widget. A workflow can be seen as a combination of services, where following outputs are passed on to the next service in the procedure without the need for human intervention. A workflow engine executes the services and connects the output of services as input to following services as defined during the configuration phase.

Hybrid-Orchestration

It can also be possible to combine the first two approaches and have a workbench which consists of widgets that execute an individual service, triggered by the human user and services that consists of multiple microservices that communicate with each other using a workflow engine.

Orchestration/Choreography by Multi-Agent-System

Multi Agent System are a part of the FAIRWork architecture and when talking about orchestration also their role in it needs to be discussed. They are organized in a decentralized way and the communication of the different agent is done following a choreographic approach. The following table gives an overview about the characteristics of orchestration and choreography approaches.

Table 1: Orchestration vs Choreography

Choreography	Orchestration
Centralized component	Distributed environment
Component know how services need to behave	Each service know how to behave
Component know how each service needs to interact	Services know how and when to communicate each other

As agents come forward on their own if their service is needed and are more event driven, they choreography approach fits better. In addition, agents can function as a connector to the digital twins and digitize physical assets.

4.3.5 Knowledge Base, Digital Twin, and Digital Shadow

Smart technologies and progress in digital technologies developed in e.g. Industry 4.0 and Industry 5.0 to change the manufacturing sector. Due to this digital transformation, vast amounts of big data is generated across the manufacturing units; from machine sensors data, to maintenance reports, production planning and scheduling data, and human work force data.

In the FAIRWork project, the "DAI-DSS KnowledgeBase" serves as a data repository. It is based on EDMtruePLM[48] where all the relevant data of products, humans, machines, robots, sensors, and sensor measurements are stored along the dimensions of lifecycle and engineering discipline. The KnowledgeBase provides an organized collection of information that is stored and shared effectively and securely. It will also include flexible and standardized integration options for data across multiple sources. Thus, it will remove duplicates, normalize, segment, and enrich data sets into custom workflows and help to orchestrate data in a unified manner. The data can be secured centrally, which will lower the risk of regulatory violations. Decisions built on data are only as good as the information used. The KnowledgeBase thus helps to provide a framework to facilitate data quality. Better data management procedures generate higher-quality information, which will enable other DAI-DSS components to make better decisions based on reliable data.

The KnowledgeBase facilitates the use of digital twins/shadows/models where all the actors like humans, robots, machines, processes and products have digital representations in EDMTruePLM. All the data related to these actors can be structured and stored in these digital models.

There are many definitions and understandings of what a Digital Twin (DT) is. Part of a DT is the virtual representation of a connected physical asset; this virtual representation focuses on some use case specific aspects of the physical twin, which may cover the entire product life cycle or parts of it. The DT mimics the structure, context and behaviour of an individual physical asset, or a group of physical assets. It may be updated with data from its physical twin in real time; data from the DT may lead to interactions with the physical twin. The value of this concept is the ability to analyse a digital environment instead of a physical environment. For example, trends in sensor measurements may help to predict and avoid undesired asset behaviour. It is important to note that DTs are not

[48] https://jotneit.com/products/edmtrueplm/ (accessed: 23-02-2023)

limited to simulations: they may use real-time data coming from the physical assets they represent; and these give an accurate picture of the current state of an asset.

The essential elements of a DT are a virtual representation (model), a physical realization (asset), and transfer of data / information (connected) between the two, including the control and actuation of the physical asset. Hence, to have a DT requires a physical asset. Models need to represent the asset properly while providing a medium for the analysis, simulation, and optimization of phenomena of interest to a use case. These models can be purely data-driven, purely physics-/simulation-driven, or a hybrid of the two. Data is exchanged across models as well as collected in real time from the physical asset by use of communication standards and protocols together with cloud-based platforms. This data can then be used for descriptive, diagnostic, predictive, and/or prescriptive analytics to inform decision making at every lifecycle phase.

While many decisions are made throughout a product lifecycle, traditionally these decisions are informed by experience about the variables that influence the ultimate performance of the physical asset. The uncertainties in the status or the external variables affecting the physical asset result in propagating uncertainties into its current or future performance. The DT harvests information collected throughout the lifecycle to update and better inform the analysis and decision-making process for the physical asset.

Digital models may include simulations of the environment and people in an area. A digital model may be, for example, a virtual three-dimensional representation of an object that can be used for simulation and analysis. A digital model may also be a functional 3D representation of a production line.

A Digital Shadow (DS) is a reduced version of a digital twin. The DS is a virtual representation of a physical asset, but there is only a one-way data flow from the physical object to its virtual counterpart; this allows the virtual model to adapt to the changing state of the physical asset. The DS gives the real time information about the status of the physical asset; it helps to interact with other DTs or DSs. An example of a DS may collect measurement data from humans by biosensors; based on this data one may derive the current stress level of a person.

DTs enable a two-way exchange of data. They consist not only of data, but may also include algorithms, simulations and services that describe or influence the properties or behaviour of the represented asset or offer services about it. The DT - in addition to the DS – may contain algorithms to predict human conditions, for example, after having experienced certain types of stress, such as, carrying heavy car parts for a long time. This information, if fed back to a decision-making component, could eventually prevent stressful situations for human beings by avoiding too much stress.

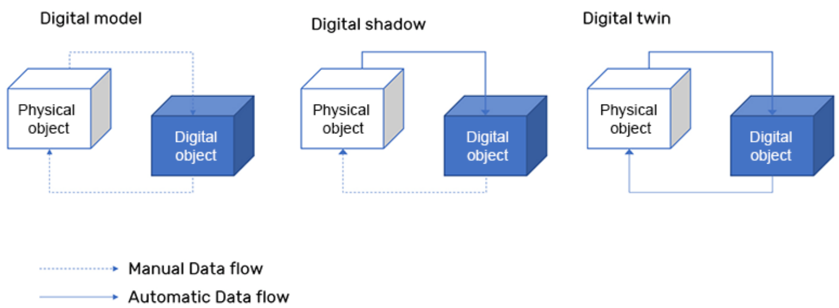

Figure 31: Schematic sketch of the concepts of digital model, digital shadow, and digital twin (from Fuller et al.49).

[49] Fuller, A., Fan, Z., Day, C. and Barlow, C. (2020): Digital Twin: Enabling Technologies, Challenges and Open Research, in IEEE Access, vol. 8, pp. 108952-108971, 2020, doi: 10.1109/ACCESS.2020.2998358

4.3.6 Experiment Laboratories for Composition and Evaluation Using the Innovation Shop

To facilitate a better utilization of the technologies discussed in chapter 3, experiments will be carried out. These experiments will evaluate, in a simplified environment, the capabilities of the technologies and support the involved project partners in better understanding the opportunities and boundaries of these technologies. The experiments themselves will be created and carried out in the corresponding laboratories (introduced below) in the context of the research method and tools (WP3) and development of the DAI-DSS (WP4). The finished experiments will then be published in the innovation shop, where project partners or other interested persons can read and recreate them.

The experiments and approaches from the laboratories should not only help to understand the technologies, but also to explain and understand how the decisions themselves are made. This can be achieved on the one side through a better understanding of the technologies themselves, based on the experiments. On the other hand, additional approaches can be created within the laboratories, analyzing how decisions can be represented so that all involved stakeholders understand them. For example, within the OMiLAB experiment environment a Scene2Model-based high-level representation of the decision-making process can support the communication and explanation of decisions, so that they are understood by involve stakeholders. This would be one research aspect that can be pursued in the OMiLAB.

4.3.6.1 Innovation Shop

An innovation shop will be established to support the exploitation within the FAIRWork project. The concept of the innovation shop will be based on the idea of existing shops, as used by the project coordinator in other EU projects, like CouldSocket[50] (cf. CloudSocket deliverable 4.1[51]) or Change2Twin[52] (cf. Change2Twin WP2[53] deliverables). Through the innovation shop, the project results can be published so that project members and third parties can use them.

On the innovation shop, we will publish innovation items, which are artifacts created in the context of the FAIRWork project, to support users in their tasks and goals. The innovation items can take on different types and range from textual descriptions to applications. For different types, different templates will be provided on the innovation shop so that the presentation of the innovation item is tailored to its type. Further, the templates define the information which must be provided to allow a publication on the innovation shop. For example, as innovation items can also be software, means of using the software should also be available. This could be the code to install it locally, a link to the service, or the integration of functionality, and similar. The concrete types depend on the innovation items which will be published in the innovation shop.

The premise is that the innovation items are self-contained, which means that they can be used independently from each other and without the need to have comprehensive knowledge of the whole FAIRWork project. Further, innovation items must not be completely finished, but can also be draft, prototypes, experiments, or similar. As long as it can create added value for possible users, it can be published. This lowers the barrier to publish useful

[50] Link to the CloudSocket innovation shop: https://site.cloudsocket.eu/cloudsocket-innovation-shop (accessed: 3-2-2023)
[51] Link to CloudSocket Deliverable 4.1: https://site.cloudsocket.eu/documents/251273/350509/CloudSocket_D4.1_First-CloudSocket-Architecture-v1.0_BOC-20150831-FINAL.pdf/0bdd6c7b-a349-47ab-bed9-631e567365d8?download=true (accessed: 3-2-2023)
[52] Link to the Change2Twin innovation shop: https://marketplace.change2twin.eu/ (accessed: 3-2-2023)
[53] Link to the deliverable list of Change2Twin: https://www.change2twin.eu/about/deliverables/ (accessed: 3-2-2023)

innovation items and reduces the burden for using them. Even though the innovation item should be self-contained, they can create synergies if they are used together.

4.3.6.2 OMiLAB

OMiLAB stands for Open Models Initiative Laboratory and offers a physical and virtual laboratory environment for model-based experiments to support the design of innovative systems. Conceptual models are used to define and capture knowledge of the experiments, not only to be understand by humans, but also to be executed in prototype environments. Models are therefore the central element of our experiments and must be tailored to meet the needs of the experiments.

Within the laboratories, we use experiments to create, understand, and evaluate the design of systems or parts of them. Experiments include the exploration and definition of the design, the creation of a prototype environment and the execution of experiment runs and their evaluation. And within these experiments models are used to describe the needed key knowledge.

To structure the experiments, OMiLAB applies a three-layered approach (Figure **32**). Each layer has a specific focus, which is supported through conceptual modelling. Additionally, each layer is supported with dedicated tools (software and/or methods). These tools can be applied as is or tailored to concrete experiments.

The top layer focuses on understanding the scenario and creating the solution idea. In this layer we apply digital design thinking to facility a thorough understanding within physical workshops and provide this knowledge with external stakeholders (which could not participate in the workshop). The main tool of this layer is Scene2Model[54], which is implemented with ADOxx[55]. Scene2Model allows the user to automatically create digital models from tangible artefacts which are created in physical workshops.

The bottom layer contains a physical or virtual prototype environment, in which the experiments are executed. The prototype must be tailored to the experiment and its context. The main tool of this layer are predefined sets of experiment settings, which can be adapted to concrete experiments.

The middle layer focuses on conceptual modelling and combines the top and bottom layer to enable synergies. The modelling methods of the conceptual models are either pre-existing (e.g., from the OMiLAB community), specifically created for the experiment, or an existing one is adapted towards the experiment. The main tool of this layer is the ADOxx metamodeling platform, which is tailored platform to create and use modelling tools.

[54] https://www.omilab.org/activities/projects/details/?id=131 (accessed: 30-01-2023)
[55] www.adoxx.org (accessed: 30-01-2023)

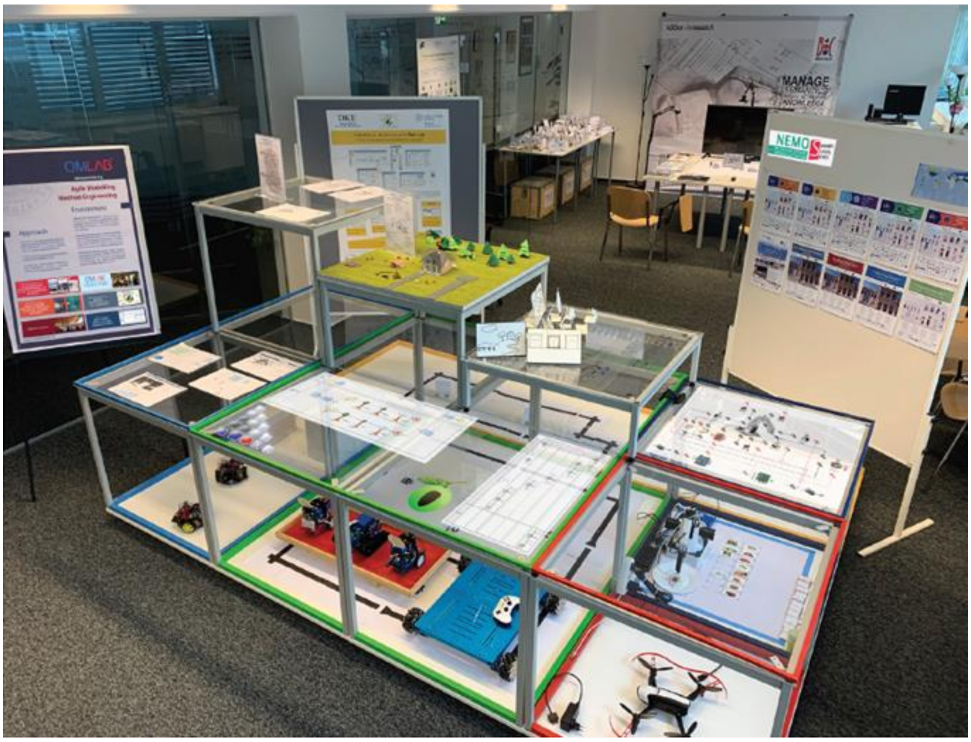

Figure 32: Example of a physical OMiLAB at the BOC innovation lab[56]

For the FAIRWork project, the experimentation environment and its tools will be utilized to create experiments of important aspects of the project and evaluate them. This includes workshops to create concrete ideas and the establishing of prototype environments to execute and evaluate the executed ideas.

To utilize the experiment environment in the context of project, a dedicated FAIRWork laboratory will be created at JOANNEUM RESEARCH, and the provided tools will be adapted. For the digital design thinking approach (top layer), will be performed enhancement of the Scene2Model tool to support a better exploration of systems, where DAI-DSS should be applied. This includes to improve the handling and capabilities of the Scene2Model tool, which will also influence the underlaying ADOxx platform.

To utilize the execution of experiments (bottom layer), the existing physical and virtual prototype environment will be evaluated and adapted to better fit the needs of FAIRWork experiments.

To utilize the modelling layer, the capabilities of the ADOxx metamodeling platform will be used create modelling tools from scratch or adapt existing ones. ADOxx has already been used as part of the OMiLAB community to realise many modelling methods[57]. ADOxx itself provides capabilities to realize modelling methods, including diagrammatic modelling languages and additional functionalities to utilize these models in various ways, like transformation, simulation, or execution.

To allow a better utilization within the FAIRWork project, the functionality of the ADOxx metamodeling platform will be enhanced, like improving the communication capabilities (protocols, service enactment and discovery) to support a more sophisticated integration with the prototype environment (bottom layer) or with tools applied in digital design thinking workshops (top layer). Other improvements are to ease the burden of the user by creating and adapting modelling methods and their tools, to better fit the needs of experiments applied in FAIRWork.

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[56] https://www.omilab.org/brochure/ - accessed 30-1-2022

[57] See https://www.omilab.org/activities/projects/ (accessed 30.01.2023) for a selection of some available ADOxx based modelling tools.

4.3.6.3 Human Factors Lab

Workspace, equipment, and expertise. The Human Factors Lab (HFL) at Joanneum Research (Figure 33, Austria, combines state-of-the-art human-centred measuring technologies with AI-enabled software for behaviour-based analytics and assessment of psychological constructs in digital systems. The HFL will be used to test certain novel technologies, be it for the measurement of reduced stress with respect to alternative decision-making pathways and interaction devices, or in the context of monotonous work that fosters fatigue and errors in the processing. In particular, in the HFL we are capable to analyse in the context of cognitive ergonomics human stress as well as cognitive, affective, and motivational state by means of mobile and wearable technologies applied at the workplace

The infrastructure is equipped to investigate psychologically relevant parameters in real-time including a wearable biosensor and Neuroergonomics workplace as – including measurement technology for high precision-oriented functional near-infrared spectrology (fNIRS) and electroencephalography (EEG) - well as VR/AR technologies, eye tracking (stationary including a 1200 Hz high precision instrument, mobile, wearable) and high precision motion capture devices, furthermore a treadmill, social robots, and software libraries for gaze-based analytics. The HFL has access to various IoT software libraries for permanent data acquisition for various sensors and gateways to set up wireless sensing network.

In the HFL we will develop a novel approach to estimating cognitive strain by studying workload related to task switching, multitasking and interruption as well as monotony effects, using wearable bio-sensor shirt, smartwatch with biosensors, eye tracking glasses, digital events and spatiotemporal patterns from human-machine interaction, etc and in relation to environmental strain, such as, insufficient air quality.

(a) (b)

Figure 33 The Human Factors Lab

The Human Factors Lab and its role in FAIRWork is depicted in Figure 33. (a) The lab embeds various workspaces. (b) Various sensor technologies and platforms are available to test human-computer interfaces and monitor psychophysiological parameters during interaction

Targeted research. Specific attention is dedicated to the development of the 'Digital Human Sensor' (DHS) applying AI-enabled Human Factors measurement technology. Each instantiation of a DHS provides a vector of Human Factors state estimates – e.g., on stress, affective state, concentration, workload, situation awareness, fatigue, etc. – with the purpose to determine cost function parameters associated with typical (inter-)actions in the work environment.

4.3.6.4 Flex Lab

Combining state-of-the-art equipment and infrastructure with Flex's broad range of topics and expertise, solutions for implementation in production are tested in the Robotic Lab of Flex.

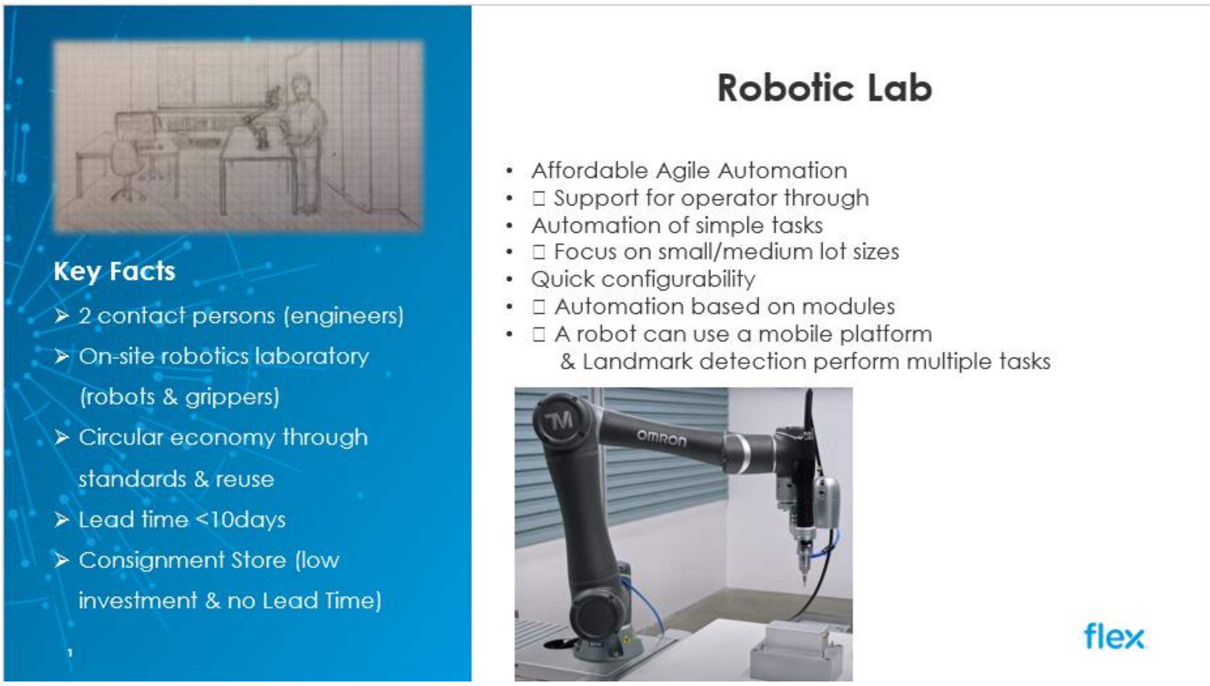

Figure 34: Flex Lab

These go beyond classic system integration and also include innovative solutions for new approaches in production. The current focus is on the implementation of collaborative robotics solutions that are rapidly deployed and implemented in production.

4.3.6.5 CRF Lab

Short Profile of Centro Ricerche FIAT SCPA

CRF (Centro Ricerche Fiat), headquartered in Orbassano (Turin) with other branch sites in Italy, was established in 1978. As a focal point for research activities of FCA (Fiat Chrysler Automobiles), CRF has the **mission** to:

- develop and transfer innovative powertrains, vehicle systems and features, materials, processes, and methodologies together with innovation expertise in order to improve the competitiveness of FCA products;
- represent FCA in European collaborative research programs, joining pre-competitive projects, and promoting networking actions;
- support FCA in the protection and enhancement of intellectual property.

Also through the cooperation with a pan-European network from industry and academia, CRF conducts collaborative research initiatives at the national and international levels in partnership with all the key public and private stakeholders concerned with sustainable mobility, targeting specifically the industrial exploitation of research.

Figure 35: CRF Lab - Impressions

CRF is in the project with the World Class Manufacturing Research & Innovation (WCM R&I) area, which specifically deals with innovation in manufacturing.
The WCM method is the structured, rigorous and integrated FCA production methodology with the primary objective to continuously improve production performance to ensure quality and improve sustainability. The WCM program aims at the excellence of the plants and of the supplier park through the dissemination of the innovative concepts developed and the use of the principles and methodologies of WCM. The role of the WCM R&I area inside the FCA WCM group ensures a wide auditory for internal dissemination and exploitation actions.
WCM R&I area is in the project mainly with the “Factory Innovation” department. The main activity of the department is the research and innovation in relation to the factory and the manufacturing process in the fields of flexibility and productivity, energy management, innovative robotics, quality monitoring, ergonomics and logistics).

Significant infrastructure/Technical Equipment

WCM R&I area is in the project mainly with the “Factory Innovation” department. The main activity of the department is the research and innovation in relation to the factory and the manufacturing processes in the fields of flexibility and productivity, innovative and cooperative robotics, quality monitoring, ergonomics, energy management and logistics. WCM R&I supports the FCA group Manufacturing Engineering in the definition, development and application of innovative technologies and methodologies in the plants. CRF has since a deep know-how of the all automotive processes implemented in FCA plants (both for vehicle and engine manufacturing), and generically in the automotive processes.
CRF WCM R&I participates in the regulatory bodies for the ISO regulation both in the field of Collaborative Robotics and Ergonomics.
CRF WCM R&I manages and performs all the innovation activities related to Exoskeletons and Collaborative Robotics development and characterization in the innovation activities of the EMEA Manufacturing engineering (both for vehicle and Powertrain manufacturing).

CRF WCM R&I main infrastructures are located in the CRF-FCA laboratories; in particular, CRF has two locations with relative laboratories: Orbassano (Flexible adaptive systems Lab; Quality process and monitoring control Lab…) and Melfi Campus (Modeling Lab, Ergonomics…).

Figure 36: Industrial Lab at CRF

At CRF four laboratories are dedicated to manufacturing aspects as:

1. Human robot collaboration.
2. Human physical interaction for cyber physical systems.

3. Manufacturing operations; it is a short assembling line reproducing the device and equipment used in automotive manufacturing plants.
4. Assembling and joining technologies concerning welding (laser, Resistance spot welding, arc welding) and mechanical joining (adhesive bonding, riveting and clinching).

Besides of the Laboratories, CRF uses many software for human simulation such as Jack, Process Simulation[58] and has developed its own software and methodologies for the analysis of HRC and Ergonomics.

4.4 Check Phase

For the check phase, a set of dashboard tools is provided to enable the specification of goals and indicators. In this step also how the indicators should be measured and the corresponding calculation method, are specified. As the companies check each project according to their official domain specific KPIs, these ratios are introduced for the FLEX and the CRF use case in the sections 4.4.1 and 4.4.2. At first, an exemplary overview of some KPIs is presented that could be reflected for evaluating the high level architecture along multiple dimensions:

<u>Domain specific KPIs</u>

- To what extent did the process improve?
- In terms of time, quality, wellbeing, etc.

<u>DAI-DSS specific KPIs</u>

- Is the DAI-DSS appropriate?
- Is the DAI-DASS sufficient?

<u>Knowledge specific KPI</u>

- Data: Is the data quality sufficient?
- Knowledge: Is there enough experience with new technologies?

<u>Social specific KPI</u>

- What is the quality and quantity of the collaboration?
- Are required experts involved?
- Is there trust?
    - Trustworthy system,
    - trust in data and knowledge,

  transparent algorithms

4.4.1 Production Use Case/Flex

This section lists the official KPIs identified by FLEX. When evaluating the User Scenario, each project in the case of Flex is evaluated according to the unified KPIs.

[58] https://www.cardsplmsolutions.com/en/products/tecnomatix/human-simulation-jack/ (accessed: 24-02-2023)

Table 2: KPI for the Flex User Scenario

Measurement	How to measure?	Critera
Quality	Each value can reach the values 0%, 20%, 40%, 60%, 80% or 100% and is a summarized value of all involved project members. The factors "Written Documentation", "Communication" and "Organization" are also taken into account.	Quality target reached
Cost	The cost rating is calculated by using complete costs (including equipment, hours) used for the project in comparison to the calculated costs for the project.	Cost target reached
Timing	Defined ratings. • **100%:** positive influence, client might start the project earlier • **80%:** no influence • **60%:** little influence to project, but no influence to client • **40%:** little influence to client • **20%:** big influence to client • **0%:** client stops the project because of timing influence	Time influence on project

The cost rating is calculated by using the complete cost (including equipment, hours,…) used for the project in comparison to the cost calculated for the project (could include updates from client, if the requirements changed during active project. If the relative costs are <20% or greater than 180% then they are set against 0.

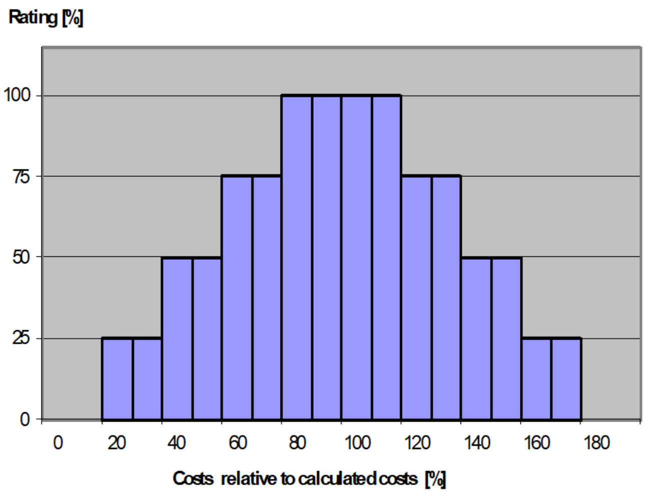

Figure 37: Use Case Flex – Cost figures for KPI

From all these parameters, the project is then evaluated and a project success factor is calculated.

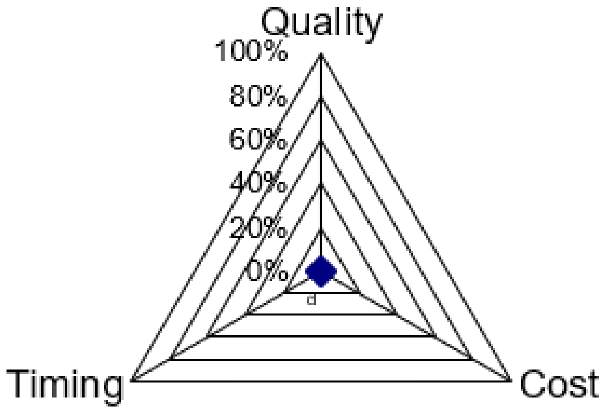

Figure 38: Project KPI Triangle

In FAIRWorks, it is planned to evaluate the research results in a very similar way.

4.4.2 KPI used in the CRF/Stellantis Scenario

This section lists the official KPIs identified by Stellantis for the stamping area, updated on 29 June 2022. They consider six macro aspects: Safety/People, Quality, Delivery, Cost, Productivity Environment/Energy.

Table 3: KPIs for the CRF/Stellantis User Scenario

Safety / People	Lost Time Injury Rate (**LTIR**)	$LTIR = \frac{\text{Number of LTI}}{\text{Total number of worked hours}} \times 1{,}000{,}000$
	Unplanned Absenteeism	Unplanned Absenteeism (%) = $\frac{\text{Total Unplanned Absenteeism Hours} * 100}{\text{Authorized Head Count x Number of shifts worked in a Month x Number of Hours per shift}}$
	Total Absenteeism Intent	Absenteeism (%) = $\frac{\text{Total Absenteeism Hours} * 100}{\text{Authorized Head Count x Number of shifts worked in a Month x Number of Hours per shift}}$
Quality	**PPM** (Parts per Million)	PPM (%) = $\frac{\sum \text{Number of apperance parts with defects claimed by customer} * 1.000.000}{\sum \text{Number of produced appearance parts}}$
	Rework Rate	Rework Rate (%) = $\frac{\sum \text{Number of repared apperance parts} * 100}{\sum \text{Number of produced appearance parts}}$
Delivery	Overall Production Efficiency (**OPE**)	OPE (%) = $\frac{\text{Actual Numbe of Strockes (Good Parts Only)} * 100}{\text{Achievable Production in Strokes}}$
	Stock Coverage (Days)	$\text{Injection Stock Coverage Days} = \frac{\left[\left[\sum [\text{Quantity of Part on hand + in transit}] * \text{standard part cost}^{**}\right] + [\text{Finished Goods}] + \text{Labor} + \text{Burden} + \text{IBT}\right]^{\text{month end}}}{\text{Daily Cost}^{\text{month average}}}$
Cost	Transformation Cost per Unit	Transformation Cost Per Unit (**€ /Ton.**) = $\frac{\text{Total Transformation Cost in a given month}}{\text{Net Metric Tons in a given month}}$
	Transformation Cost per stroke per line	Transformation Cost Per Unit (€ /Strokes) = $\frac{\text{Total Transformation Cost in a given period calculated per each line}}{\text{Number of stockes per line produced in a given period}}$
	Industrial Stock	$\text{Industrial Stock} = [\text{Gross Industrial Stock Perimeter valued monetarily}]$- Foud Net
Productivity	**ADCT** – Average Die Changing Time	ADCT = $\frac{\sum \text{Die Changes Time}}{\sum \text{Die Changes}}$
	ASPH – Average Stroke per Hour	ASPH = $\frac{\sum \text{Strokes}}{\sum \text{ETP (Effective Time of Production)}}$
	Loading rate	Loading Rate (%) = $\frac{\text{ActualProduction (Strokes)} * 100}{\text{Capacity (Strokes)}}$
Environment / Energy	Energy Consumption	ENERGY (kwh/Ton) = $\frac{\text{Energy consumption (KWh)(electr.+ gasLHV+steam+hot water +coke)}}{\text{Total Gross Metric Tons}}$

Lost Time Injury Rate (LTIR) is defined as the ratio between the number of Lost Time Injuries (LTI) and the total number of worked hours, multiplied by one million.

Intent: Drive accountability and reduction of permanently disabling injuries and serious injuries and fatalities (SIF) within our manufacturing and non-manufacturing operations and reduce the impact of these injuries on our business.

Total unplanned absenteeism is defined as total person-hours (paid, unpaid) where the hourly worker was not at work as expected. “Unplanned” refers to the employee calling in on the day they are expected to be at work and declaring their intention of not being there or being late or in worse case not calling in.

***Intent*:** Drive reduction in total unplanned absenteeism, as it directly affects the performance of the plant which results in:

- Potential losses (throughput, quality) due to non-standard worker performing the work.
- Potential overmanning due to inability to predict the unplanned portion of total absenteeism.
- Inconvenience and additional non-value planning work to get the line running at the beginning of the shift.

Total absenteeism intent is defined as total person-hours (paid, unpaid, planned, unplanned) not worked by hourly employees, who would normally be expected to be at work. People expected to work refers to the authorized Stellantis headcount for a specific plant during the time period being analyzed.

Intent: Drive reduction in total absenteeism, a daily management challenge, which results in:

- Potential losses (throughput, quality) due to a non-standard worker performing the work.
- Potential overmanning due to inability to predict the unplanned portion of total absenteeism.
- Additional non-value-added planning work, even if the absenteeism is planned.
- Management organizing the team in order to limit disruptions.

The indicator **PPM measures** the amount of anomalies for every million parts produced in the stamping shop. The measurement is carried out based on the parts that were found to be defective and that were claimed by our customers (internal or external).

Intent: Defines a metric to monitor the quality of products sent to the customer, whether it is a customer internal or external to the Plant.

Rework Rate (%) is related to the number of repaired appearance parts divided by the total number of produced appearance parts.

Intent: The Rework Rate measures how much rework takes place in a process. It is therefore an indicator of internal operational efficiency. It measures the number of parts that require rework.

Overall Production Efficiency measures the ratio of actual number of good units produced compared to maximum achievable units.

Intent: Drive efficiency of process and asset utilization.

Stock coverage indicates the average number of days of consumption/production the current direct stock can cover. It is calculated by dividing the Direct Stock level including stamping finished goods at the end of the month by the average cost of production per day of the given month.

***Intent*:** Measure the speed in which Stellantis consumes the inventory available in a given central Stamping plant.

Transformation Cost per unit is the total transformation cost divided by the total units produced in a given period.

***Intent*:** Drive reduction in transformation cost per unit, thereby, improving company profits and stakeholder value.

Transformation Cost per stroke per line is defined as total transformation cost calculated per each stamping line divided by the number of strokes produced by this specific line (including blanking lines).

Intent: Drive reduction in transformation cost per each stroke on each line, thereby, improving company profits and stakeholder value.

Industrial Stock measures the monetary gross value of the Stock (or, Work-In-Process inventory) owned by Stellantis for a given plant. Stock for a plant includes both raw material/components in the plant, off-site warehouses, by 3rd party, and material in-transit to the plant (see more details in "Stock Coverage Days" KPI).

Intent: Drive reduction in cash tied up in surplus work-in-process inventory

Average Die Change Time is defined as the average time to change the tool on the device or equipment.

Intent: Drive increased plant production capacity based on set-up related activities, improving losses related to availability, performance and quality.

Average Strokes Per Hour is defined as the average number of strokes that the Press Line can make in one hour.

Intent: Drive increased plant production capacity based on Press speed.

Loading rate measures the ratio between the strokes performed versus the capacity (strokes) according to the maximum production achievable at the end of the year (target EOY) to each equipment and tools, according to the definition of hours (6100 hours/year).

***Intent*:** The loading rate measures the saturation of manufacturing assets in production processes.

Energy Consumption is a measure of the total energy consumed by a facility to produce a vehicle. All forms of energy consumed (electric or thermal), whether purchased from service providers or internally produced through co-generation, needs to be accounted for when reporting this metric. In addition, all energy used by onsite service providers needs to be included in the computation.

***Intent*:** Drive reduction in total energy consumption (electricity, natural gas, heating fuels) used to produce vehicles.

4.5 Act Phase

In this phase, we reflect and review the learning steps of this iteration. If it does not work well, we adapt our approach with a different plan again. If it is successful, we incorporate what we learned from the iteration into further changes. We use what was learned to plan new improvements and run the next iteration.

For example, some reflection points can be and are not limited to:

The use case with processes:

- Can DAI-DSS help here?
- Is it the appropriate approach?

The configuration of decision making:

- The selected models.
- The generated models.
- The interpretation of the model.

- The actual performance of the system.

The processes:

- The users as decision maker.
- The used AI-services.
- The interpreted data.
- The performance of the technology.

User Interface:

- Self-Configuration and flexibility.
- Back-end AI and Data Algorithms.
- Data and Knowledge Repositories.
- Infrastructure, Integration and Cloud capabilities.

After thorough reflection of the use case, the selected AI approach and the realized system, the PDCA cycle starts over again with the next planning phase for an improved execution in the “do-phase”. All phases are incrementally adjusted until the desired output is reached.

5 INITIAL HIGH LEVEL ARCHITECTURE

In chapter 5, an **outline of the initial architecture of the project** is given based on the overall project objectives and requirements. Key components of the FAIRWork service framework are motivated, described and their relevant features are presented. A detailed description of the initial architecture is given in Deliverable D4.1 including the technical implementation of the basic core services or application specific services.

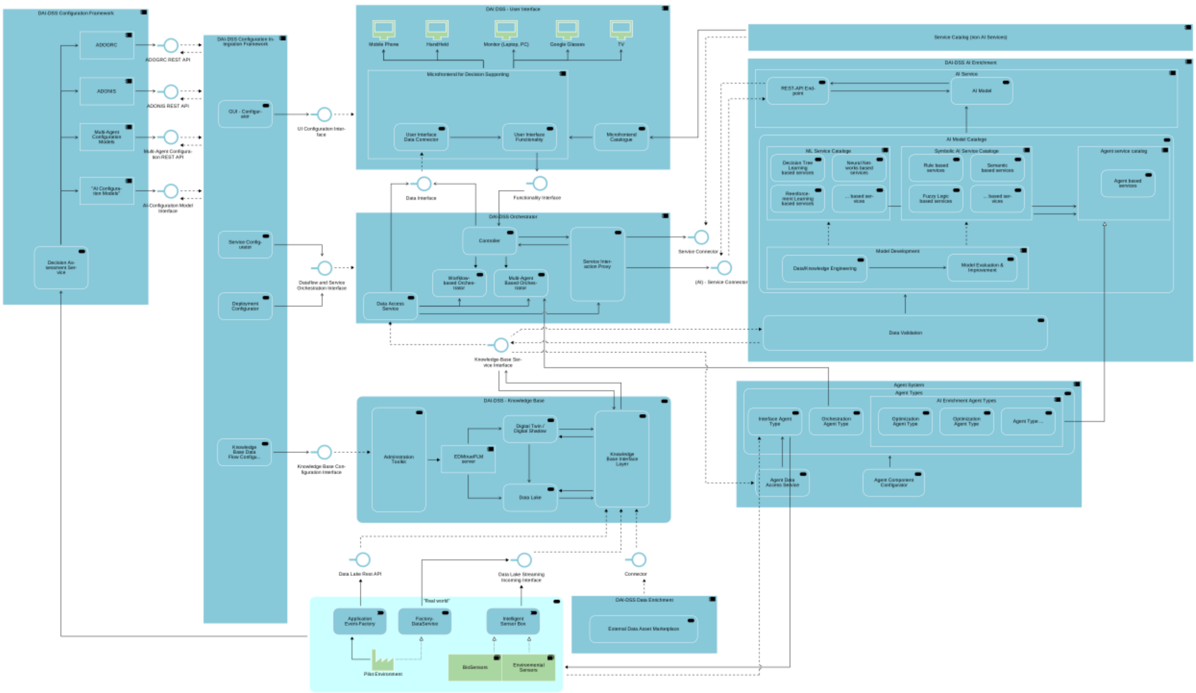

Figure 39: Overview of high-level architecture (full size image at Annex A.18)

5.1 DAI-DSS User Interface

The DAI-DSS User Interface plays a significant part in the decision-making process because itshould provide a clear picture of the alternatives and possibilities available to the decision makers and provide a supportive environment. These user interfaces can be shown on a variety of devices, depending on the working environment and circumstances, to suit the user's needs. Examples of devices, where the user interfaces could be displayed are mobile phones, tablets, laptops, Google Glasses, or TVs.

The display of relevant KPIs or other information and the provision of user interaction for the decision maker are the two main functions of the user interfaces. Monitoring multiple statuses in a production hall is an example of where the presentation of KPIs may be useful. Interacting with the system becomes relevant when a service for fulfilling a certain task (e.g. worker allocation using fuzzy rules, simulation using a multi agent system etc.) is needed and thereby started by the user to support the decision-making process. The user interface can be envisioned as a type of “workbench”, where different services relevant for the use case scenario are provided. Some of these services known as widgets can be triggered by the users whenever they need them, while others are not interactive and provide only a graphical representation of information. The use of these configurable widgets enables a customized representation reaching from simple overview tables to including KPIs into pictures. Which widgets are needed and how the KPIs are presented is specified through a subcomponent of the DAI-DSS Configurator Integration Framework component: the GUI Configurator.

The frontend and backend of the user interface are based on OLIVE[59], a model-aware microservice framework. All available micro frontend services are stored in a form of a catalogue and the user interface can be created by choosing and adjusting relevant services using the configuration framework. The frontend consists of two subcomponents: the User Interface Data Connector and the User Interface Functionality. The former interacts with the backend micro services, known as connectors. Connectors need to be configured like the frontend widgets and the configuration of them creates a new instance, which can access data sources and external systems. External sources to obtain data from could be the Knowledge Base, Multi Agent Systems or AI services. The accessing of data for the User Interface is done via the DAI-DSS Orchestrator component using the Data Interface. The User Interface Functionality subcomponent provides additional functions to the User Interface (e.g. sorting or filtering data entries). This subcomponent communicates with the DAI-DSS Orchestrator component via the Functionality Interface.

The DAI-DSS User Interface component is highly dependent on the DAI-DSS Configurator and on the DAI-DSS Orchestrator. The configurator acts as an intermediary component to provide model awareness for the user interfaces. In addition, the configuration environment gives the opportunity to configure the frontend microservices and their representation. The DAI-DSS User Interface rely heavily on the orchestrator since it gives users access to the data that must be displayed. This data may originate from the knowledge base or may be the result of various services or of the multi agent negotiations.

To enable the creation of widgets that fulfil decision makers' needs and can provide access to AI services or Multi Agent Systems, an already existing KPI design tool should be enhanced. The current tool was built using ADOxx, a meta-modelling platform and enables the definition of goals, sub-goals and KPIs using a model approach. Based on this model different widgets for the web application can be created. The current models and widgets need to be adapted to create user interfaces that support decision making more efficiently.

5.2 DAI-DSS Configurator

The DAI-DSS Configurator is an intermediate component, which connects various model environments with the user interfaces and the orchestrator component of the DAI-DSS system and enables their model awareness. Such model environments can include the creation of process models, dashboard models and models for the configuration of Multi Agent Systems and AI. The configurator combines the different types of models and generates decision models out of it, containing the configuration information for the other components in the system. One part of the configurator concerns with the decision assessment. This means that decision models can be evaluated using various assessment tools, e.g. questionnaires or polls. If a model got approved, it gets signed digitally to prevent subsequent changes. Besides the assessment of models a laboratory environment makes part of the configurator. The laboratory experimentation gives access to the experiments via an interface, enabling the entry of real-world data for experiments on the one side and the execution of experiments during a decision-making phase on the other.

The internal architecture of the DAI-DSS configurator is based on the OLIVE microservice framework. Due to OLIVEs pre-built interaction with the meta modelling platform ADOxx, the appearance and functionality of the decision support system can be created by drawing models. Models of various types coming from different model environments serve as input for the configurator. After combining these different kinds of inputs to decision models, they are processed by the internal subcomponents. There are four different subcomponents and each of them extracts information from the decision models depending on the component and purpose it needs to create an output configuration file for. From the configuration file instances of microservices can be created to fulfil specific tasks. Important model data for the DAI-DSS User Interface is provided by the GUI Configurator. This subcomponent extracts data necessary for the design of customized user interfaces, by configurating microservices

[59] https://www.adoxx.org/live/olive

for the front and back end. This configuration information could specify how data should be rendered on the monitoring user interfaces as well as how warnings should be displayed or what colours to use when a KPI value exceeds a certain threshold. Another subcomponent of the configurator is the Deployment Configurator, which provides configuration files for the DAI-DSS Orchestrator. This component can obtain data regarding both the deployment of individual microservices as well as the combination of such services to fulfil the required business functionality. The DAI-DSS Orchestrator gets input from a second subcomponent: the Service and Dataflow Configurator. The Service and Dataflow Configurator extracts which data and services should be triggered to identify appropriate solutions for the decision maker. The orchestrator receives the pertinent model data from this subcomponent, processes it, and then takes action depending on the information. The fourth subcomponent is the Multi-Agent Configurator and it adjusts the required agents and obtains the necessary data from the agent model. This agent model is sent to the Multi Agent System as a connector structure. The header of the agent accesses the decision model's information and modifies it as necessary to comprehend it.

The provision of the configuration files makes the DAI-DSS Configurator a very important component for other parts of the decision support system. The DAI-DSS User Interface and the DAI-DSS Orchestrator are highly dependent on the configurator and the knowledge base is connected as well as it stores the decision models after their assessment. The input data for generating the various configuration files for the dependent components is coming from the different model environments using REST APIs. To connect the configurator with the DAI-DSS User Interface the Dashboard Configuration Interface is used. The Dataflow and Service Orchestration Model links the configurator to the DAI-DSS Orchestrator, while the configuration information is delivered to the Multi Agent System using the Multi Agent Configuration Interface.

As already mentioned above the configurator is based on the OLIVE framework and this framework must be enhanced for this project by creating connectors that can launch AI services, processes, and Agents depending on configuration files produced by decision models.

5.3 DAI-DSS AI Enrichment

The AI enrichment in DAI-DSS is a colletion of services, which consists of various AI-algorithms and models that contribute to decision-making by being connected in Multi Agent System (MAS). The main role of the AI enrichment in the DAI-DSS environment is to provide a collection of knowledge and data-driven models, which enrich current decision making. The principle is to use traditional AI-algorithms as well as machine learning and agent based approaches. Each of such models or optimisation algorithm contributes in the decision-making process bringing closer the decentralised and fair approach. In the DAI-DSS environment, AI Enrichment communicates with the DAI-DSS Knowledge Base via REST-API, which allows data to flow between the two services.

In general, AI enrichment services implements six main parts:

- Data validation – in this phase, the data available for a specific use case is verified in terms of quality and quantity. It is important to ensure the correctness and meaningfulness of the data as well as its digital format, which can be further used in model development.
- Model selection – in this phase, the model for representing the agent is selected. Some possible methods that may be used are reinforcement learning (RL), decision tree (DT), artificial neural networks (ANN), and semantics. The choice is based on the objectives of the use case and the available data, its type, quality and size. Furthermore, the data is validated against the initial model concept and, if necessary, the model concept can be readjusted to meet the requirements.
- Model development – in this phase, the previously collected data is applied in a selected model to mimic the agent's behaviour or to optimise the system. The available data may require individual preparation to be suitable for further model training. Depending on the needs, this phase may consist of data cleaning,

normalisation, scaling and feature engineering. In addition, the model is evaluated and adjusted to achieve the highest possible quality of predictions.

- Model application – the resulting model is prepared to be applied on actual, real-time data where a request to receive the prediction for an individual agent is communicated via TensorFlow serving.
- TensorFlow serving – is a flexible machine learning model serving system designed for production environments. It makes it accessible to deploy new algorithms and models while maintaining the same server architecture and APIs. TensorFlow Serving provides the integration with TensorFlow models as well as with other types of models and data.
- REST-API serving – In general, not all AI models can be deployed using Tensorflow serving. If an AI model is incompatible with the Tensorflow conventions, it is provided via a dedicated REST API endpoint.

Moreover, there are parts of the intelligent enrichment carried out on the edge because of privacy aspects. In the context of the FAIRWorks project, there is a need to provide part of the infrastructure within the factory, like the intelligent sensor box, placed between the main sensor network and the factory infrastructure. Due to the requirements in the production industry and the privacy aspect of the human aspect, the intelligent sensor box also needs the ability to analyse data. Edge analytics is a model of data analysis where incoming data streams are analysed at a non-central point, near the sensor network or other data sources. Data can be prepared and filtered on the edge layer (e.g. within the factory). This reduces the amount of data for the centralised decision service layer. Finally, specific visualisations for parts of the sensor or infrastructure within a factory could be provided in this layer. This software component – herein it is referred to as an Intelligent Sensor Box – supports local data management and data analysis. Depending on the use case, different forms of data analytics such as time-aware graph, logical and statistical reasoning as well as edge AI methods, are supported if necessary. The Intelligent Sensor Box will assist users in local decision-making. This component should also be capable of dealing with limited resources (e.g. network bandwidth, data storage). In such cases, the overall functionality may be decrease.

5.4 DAI-DSS Orchestrator

The DAI-DSS Orchestrator is critical to the overall execution of the decision support system because it manages and coordinates the configured services and workflows needed to providing decision-making options for the end user. Services can be standalone or linked in the form of a workflow. While in the first case, the orchestrator is responsible for simply calling the individual service and retrieving the necessary data from the Knowledge Base, the second option is more complex due to the involvement of more services. A workflow engine or a multi-agent system handles the orchestration in the latter case. For most of the services in the FAIRWork project the workflow-based orchestration will be sufficient, but when the task requires very high flexibility the multi-agent system could be a more adequate approach. This could be the case when we deal with communication between autonomous entities that negotiate interests among their peers, because it allows an intelligent and distributed control and monitoring of the task execution.

The key part in the orchestrator plays the Controller. This component allows to manage microservices and controlling their whole lifecycle. The controller component allows to start a microservice instance, to keep it running in an isolated environment, to stop it, and dismiss it. The orchestrator component is dependent on the DAI-DSS Configurator as it generates microservice instances based on configuration files provided via the Dataflow and Service Orchestration Interface. It also provides and receives data from the User Interface, as services can be triggered through user interaction and results need to be displayed. In addition to that, it is connected to AI and non-AI service catalogs by the Service Interaction Proxy. If this services need input data, the orchestrator can access the Knowledge Base to retrieve it using the Data

In a summary, the DAI-DSS Orchestrator has numerous interactions with its surrounding DAI-DSS modules in order to streamline the way information flows through the system and organize the way communication can happen so that the competencies of each module are properly appreciated. The challenge is to harmonize the featuresof each part in the system.

5.5 DAI-DSS Knowledge Base

The DAI-DSS Knowledge Base is a central part of the DAI-DSS architecture. It acts as a centralized repository for the majority of data involved in a decision-making configuration. A decision-making process requires data from a wide range of different sources and produces results. The Knowledge Base is intended to collect all necessary data sets and streams, structure them, potentially merge them, store them, and then provide an interface layer which allows other DAI-DSS components to harvest said data. To enable AI algorithms to properly learn from previous decisions, and to enable processes to use earlier results, also such decisions and results are stored in the Knowledge Base.

The DAI-DSS knowledge base is composed of the following concepts: Digital Twin and Data Lake. The Digital Twin concept is defined differently in different contexts across industries and academics. In the context of the FAIRwork project we consider the Digital Twin definition to be "… a digital replica of an artefact, process or service that is so accurate that it can be used as basis for taking decisions. The digital replica and physical world are often connected by streams of data."[60.] The definition used in the project for Data Lake is the following "A data lake is a concept consisting of a collection of storage instances of various data assets. These assets are stored in a near-exact, or even exact, copy of the source format and are in addition to the originating data stores.[61]

The implementation of the Knowledge Base is done in Jotne's PLM application EDMtruePLM[62]. The application is based on the ISO 10303 standard[63] and serves as a repository that collects product lifecycle data, including manufacturing and sensor data, from various heterogeneous resources. The semantics of the data streaming into the repository are mapped to the comprehensive high-level ontology of STEP (ISO 10303). Individual interface components may be added to translate source data from applications into this target representation. The repository will be enhanced with merge and validation algorithms to create a consistent data set out of the heterogeneous input streams.

The implementations of the ISO standards in EDMtruePLM have been designed for the concurrent engineering requirements of high technology industries like aeronautics, space, and defense. However, care has been taken to enable adaptation to other engineering domains. This has been achieved by the so-called 'reference data', which a project manager or a specific reference data manager may define to configure a project. Thus, use case and project domain specific terms are assigned for example to sensors, products, product and project breakdown elements (also called nodes) and documents, and their properties, roles, lifecycle phases etc..

EDMtruePLM provides a REST API for its database to get, add or edit content. In addition, it can also integrate the Arrowhead framework[64] (an IoT framework for making sensors and applications interoperable) for communicating with other Arrowhead compliant components. It is up to the components of the FAIRWork architecture to select their way of communication with the DAI-DSS Knowledge Base. It is envisaged that initially the REST API will be

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60 Felsberger, Andreas; Oberegger, Bernhard; Reiner, Gerald (2016): A Review of Decision Support Systems for Manufacturing Systems. In: SamI40 workshop at i-KNOW.

61 Fuller, A., Fan, Z., Day, C. and Barlow, C. (2020): Digital Twin: Enabling Technologies, Challenges and Open Research, in IEEE Access, vol. 8, pp. 108952-108971, 2020, doi: 10.1109/ACCESS.2020.2998358.

62 https://jotneit.com/products/edmtrueplm/

63 Rabta, Boualem; Reiner, Gerald (2012): Batch sizes optimisation by means of queueing network decomposition and genetic algorithm. In: International Journal of Production Research, 50, 2720 - 2731.

64 ISO 12006-2:2007, Framework for object-oriented information

used. The Arrowhead Framework or other existing IoT frameworks may be considered throughout the project. Potentially only parts of the Arrowhead Framework, such as the MQTT-protocol or other specific protocols for more performant data streaming in and out of the Knowledge Base will be studied and implemented if beneficial for a specific use case.

The DAI-DSS Knowledge Base stores data in accordance with the ISO 10303-239 (AP239), "Product lifecycle support" (PLCS) data model. The PLCS data consists of about 470 entity data types, which one may also refer to as classes.

The DAI-DSS Knowledge Base instantiations of the PLCS data model will include classifications of the instances, both the assignments and the class names. These classifications use the terms of the reference data library (RDL). Also the RDL will be part of the DAI-DSS Knowledge Base repository; the reference data are, however, stored according to a different data model, that is, the one of ISO 12006-3, "Framework for object-oriented information". The following Figure **40** shows how reference data from external OWL ontologies are loaded into EDMtruePLM. The reference data that are used in a PLCS population must be present also in the RDL population. For data exchange, both populations need to be communicated together.

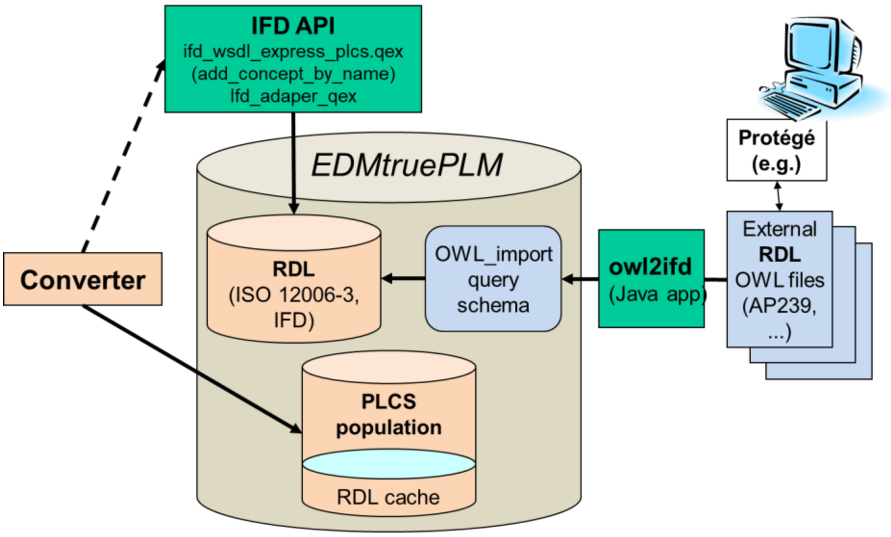


Figure 40: The EDMtruePLM repository architecture with PLCS data and RDL in different data models

5.6 DAI-DSS External Data Asset Marketplace

The purpose of this component is to provide a data catalogue. It can be seen as an extensible metadata platform to support for data practitioners to leverage the value of data within their organization and developers to tame the complexity of their rapidly evolving data ecosystems. First, it simplifies the management of metadata. Second, it makes data sets more easily searchable and usable. This is achieved by collecting and indexing metadata from different source systems in data catalogues. In this way, the suitable data stocks become more easily reusable and usable for business and research applications. Finally, it is also about helping data experts to quickly find the most suitable data e.g. for training an AI algorithm, for testing an algorithm, and for demonstrators and labs to make data-driven technology more usable and presentable.
These shared results have an additional value for all participants in such a data asset market. Analyses, such as Immonen et al.[65], have identified key roles in a data ecosystem, as described below:

- The Data Provider (DP) is an entity (data platform / natural person) that has data in whatever form and delivers it on demand or shelves it at the Broker.

[65] Immonen, A.; Palviainen, M.; Ovaska, E., "Requirements of an Open Data Based Business Ecosystem," in *Access, IEEE* , vol.2, no., pp.88-103, 2014

- A Decision Making Service Provider (SP) creates services such as enrichment / optimisation services / visualization, which are provisioned by an infrastructure provider.

However, this component is based on a data assets catalogue, where items can be provided from external resources in a service-based manner to be used by various service-based infrastructures. The component provides several functionalities. First, it includes a set of features for discovering and managing your data assets, e.g. user registration, search of data assets, ingest and describe data asset etc. Second, the search function supports several standard features, for example, the search terms will match against different aspects of a data assets. This includes asset names, descriptions, tags, terms, owners, and even specific attributes like the names of columns in a table. Third, it enables a powerful way to annotate entities within FAIRWork data asset market place.

6 COMPARING THE INITIAL ARCHITECTURE OF FAIRWORK WITH OTHER INITIATIVES

In the final chapter, the initial outline of FAIRWork's architecture is compared with relevant other European initiatives and their architectures that are commonly used in the industry relevant domain, such as, Gaia-X, FIWARE, International Data Space, and RAMI. There, we also point out the missing components for complex decision making in these initiatives.

6.1 GAIA-X – Reference Initiative

The Gaia-X[66] project aims to build a European-based, open data infrastructure that prioritizes data and cloud sovereignty. The project's goal is to establish common standards, best practices, tools, and governance mechanisms for data sharing, as well as an EU-centered federation of cloud infrastructure and data services.

One of the main goals of Gaia-X project is to enable data and infrastructure ecosystems. This requires a model for operation (i.e., Gaia-X Operational Model), model for interaction in a service-based infrastructure (Gaia-X Federation of Services), and a trust model (i.e., Gaia-X Operational Model). A digital ecosystem can be built on these foundations. An ecosystem is a system of actors and their environment that interact and function as a whole, like a biological ecosystem. In a technical context, it refers to a group of loosely coupled actors that work together to create an economic community and its associated benefits.

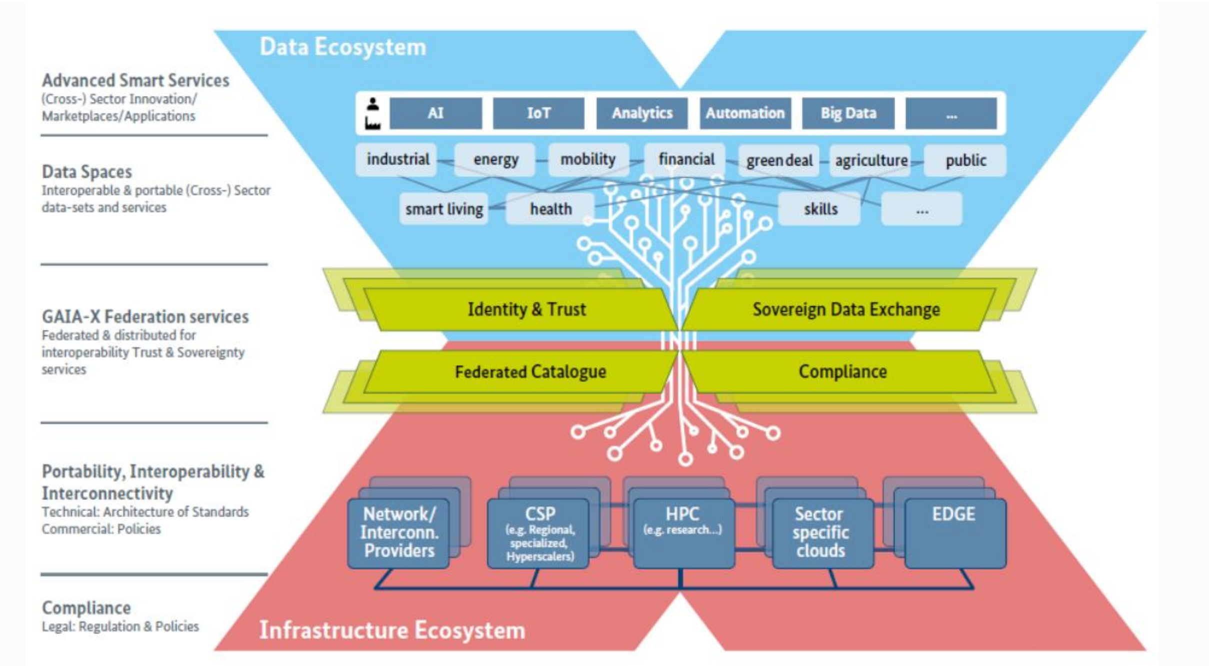


Figure 41: Architectural Concepts of the Gaia-X Core Services. Source BMWi[67]

The Gaia-X project proposes to structure a Data Ecosystem and an Infrastructure Ecosystem, each with a different focus on exchanged goods and services. However, they are not separate and build upon each other. The Gaia-X Ecosystem is made up of all individual Ecosystems that use the Gaia-X Architecture and conform to Gaia-X

[66] Gaia-X Initiative. https://gaia-x.eu/ (accessed: 15-02-2023)
[67] Source: https://homo-digitalis.net/how-gaia-x-could-enable-a-european-data-economy/. (accessed: 15-02-2023)

requirements. There may be multiple individual ecosystems, such as Catena-X[68] in the automotive sector, that use the architecture and may or may not use the federation services open source software. The basic roles of consumer and provider are visualized as different squares, while the federator appears as a connecting layer, offering diverse core federation services. Federation services provide connections between and among the different elements as well as between or among the different ecosystems. Governance includes the policy rules, which are statements of objectives, rules, practices or regulations governing the activities of participants within the ecosystem. Additionally, the architecture of standards defines a target for Gaia-X by analysing and integrating already existing standards for data, sovereignty and infrastructure components.

The Gaia-X initiative cannot be directly compared with FAIRWork. It only shows us that in order to be able to build a decision-making system, we have to build up and maintain the data and the knowledge in any case. The core elements of the original elements may also be relevant in FAIRWork.

Mapping of sine FAIRWork's core components of the architecture to Gaia-X:

- The **DAI DSS Knowledge Base** is mapped to the data ecosystem in the asset section. We build on data from the industrial domain and collect it in an unstructured way (e.g. data lake) and build up knowledge in a structured way (e.g. digital shadow/digital twin part).
- The **DAI-DSS AI Enrichment** can be mapped partly to the smart services. However, there are no explicit services for decsision making such as in FairWork. This a key difference to Gaia-X.
- The participants part can be mapped to the **DAI DSS User Interfaces**. In this way, the user can interact with the services.
- The **real-world part** can be mapped to the infrastructure ecosystem section. In FAIRWork, we use here the infrastructure which is deployed in the production domain.

6.2 FIWARE – Reference Architecture

FIWARE[69] is a set of open source software components that can be used to develop smart solutions for industry, smart city, and the Internet of Things. The components, known as "Generic Enablers", provide a common framework for building applications and services that can be easily integrated. Some of the key features of FIWARE include support for big data, IoT, and cloud computing, as well as built-in security and privacy features. It is a global initiative aiming to accelerate the development of smart data models by providing a common platform and using OPEN APIs for the development of smart applications and services, using open source technologies.

In order to create platforms that facilitate the development of smart solutions quickly, easily, and affordably, FIWARE offers a curated framework of open source software platform components that may be put together individually and in combination with other third-party components.

[68] https://catena-x.net/de/ (accessed: 22-02-2023)
[69] https://www.fiware.org/ (accessed: 22-02-2023)

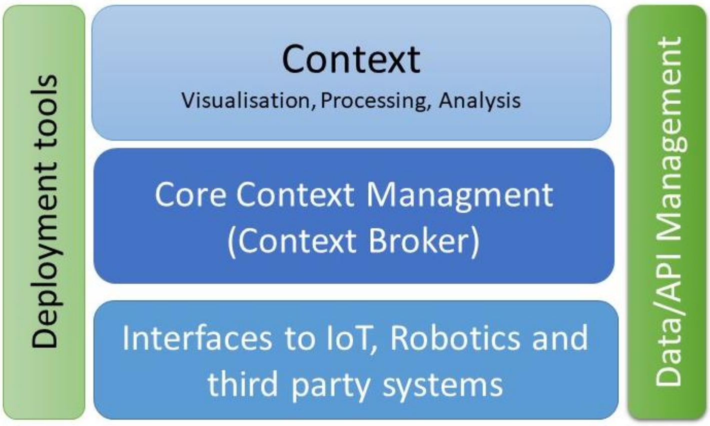


Figure 42: FIWARE – Functional Building Blocks. Source: JR

A FIWARE Context Broker Generic Enabler serves as the primary and only required component of any "Powered by FIWARE" platform or solution. It provides the fundamental function necessary for any smart solution: the need to store context information, enable updates, and provide access to context.

A rich suite of complementary open source FIWARE Generic Enablers, built around the FIWARE Context Broker, is available, dealing with the following:

- **Interfacing with the Internet of Things** (IoT), robots, and third-party systems in order to capture context information updates and translate required actuations.
- **Data/API management**, publication, and monetization, enabling usage control and the possibility of publishing and monetizing a portion of managed context data.
- **Processing, analysis, and visualization** of context information in order to implement applications' expected smart behaviour and/or assist end users in making smart decisions.

You can use these enablers or combine them with third-party components to design the platform of your choice.

Mapping of some FAIRWork' core components of the architecture to FIWARE:

- The **DAI-DSS User Interfaces** can be mapped to the visualization functions in FIWARE.
- The **DAI-DSS AI Enrichment** can be mapped to the processing and analysis part. In FAIRWorks, we have clear focus on AI enabled services. This is a difference to FIWARE.
- The **DAI-DSS Orchestrator** can be partly mapped to the core context management functions.
- The **DAI-DSS Knowledge Base** can be mapped to the Data/API management. However, there are no explicit services for decision making such as in FairWork. In FIWARE, we do not make a difference between data and knowledge. However, this is very important in FAIRWork.
- The **real world part** can be mapped to the Interfaces to IOT, robotics and 3rd party systems.
- The **DAI-DSS Configurator** can be mapped to the deployment tools section.

6.3 Industrial Data Space – Reference Architecture

The International Data Spaces (IDS)[70] is a platform that enables secure and standardized data exchange and data linkage within a trusted business ecosystem. It facilitates the creation of smart-service scenarios and innovative

[70] https://internationaldataspaces.org/. (accessed: 22-02-2023)

cross-company processes, while ensuring that data owners retain control over their data. IDS leverages existing standards and technologies, as well as governance models that are widely accepted in the data economy.

The IDS initiative is divided into several layers, each with specific functionality: the data layer, communication layer, service layer, application layer, and management layer. It is focused on providing trust, security and data sovereignty, a decentralized approach for data storage and the integration of domain-specific data vocabularies.

The IDS initiative is divided into three types of activities: research activities, standardization activities, and activities for the development of products and solutions for the market. Fraunhofer [71] runs the Strategic Initiative Data Spaces as a large internal research program aiming at the design and continuous development of the core principles of the IDS Reference Architecture Model (IDS-RAM). The International Data Spaces Association (IDSA), a non-profit organization, aims at promoting the IDS-RAM in order to establish an international standard. Actors in the market can make use of the International Data Spaces standard for providing software services and technology to the market and ensuring compliance with the International Data Spaces standard, it must undergo a certification process.

[71] https://www.dataspaces.fraunhofer.de/en/InternationalDataSpaces.html. (accessed: 24-02-2023)

Components:

- **Business layer:** The Business Layer of the International Data Spaces Reference Architecture Model defines and categorizes the different roles of participants in the IDS and specifies basic patterns of interaction between these roles.
- **Functional layer:** The Functional Layer of the International Data Spaces defines the functional requirements and features that need to be implemented, regardless of existing technologies and applications. It outlines what the IDS should be able to do, and sets the functional specifications for the IDS.
- **Process layer:** The Process Layer of the International Data Spaces Reference Architecture Model outlines the interactions between the different components of the IDS. It provides a dynamic view of the architecture by describing the main processes that take place within the IDS.
- **Information layer:** The Information Layer of the International Data Spaces specifies the Information Model, which is the common language shared by the participants and components of the IDS. It facilitates compatibility and interoperability, enabling (semi-)automated exchange of digital resources within a trusted ecosystem while preserving data sovereignty of data owners.
- **System layer:** The System Layer of the International Data Spaces maps the roles defined in the Business Layer to a concrete data and service architecture that meets the requirements specified in the Functional Layer. It forms the technical foundation of the IDS and is responsible for implementing the technical specifications of the IDS.

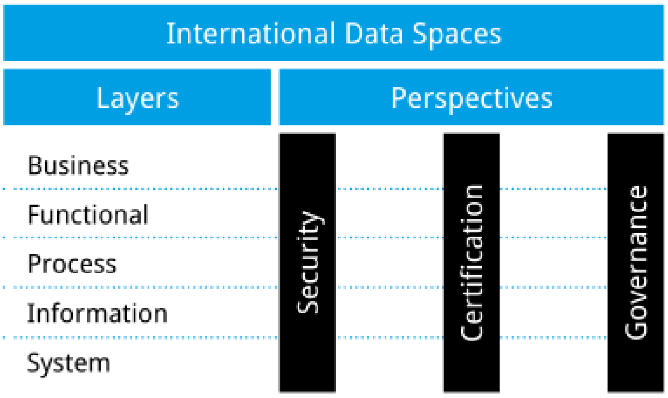


Figure 43: Functional building blocks of the International Data Spaces. Source IDS.

The IDS is mainly focused on all type of data including secure data sharing and data exchange. FAIRWork concentrate on complex decision making where data is just one part.

Mapping of some FAIRWork core components of the architecture to the IDS:

- The **DAI-DSS User Interfaces** are mapped to the business.
- The **DAI-DSS AI Enrichment** are partly mapped to the functional and process layer. There the implementation of services on the data. In FAIRWork, the AI enrichment is applied on data and an generated knowledge by humans and services. This is a clear difference to the IDS initiative.
- The **DAI-DSS Configurator**, creating configuration files for microservices, is mapped to the Process.
- The **DAI-DSS Knowledge Base** is mapped to the Information layer in IDS.
- The **real-world part**, handling real-world data, is mapped to the System.

6.4 RAMI – Reference Architecture

RAMI 4.0, also known as "Reference Architecture Model Industry 4.0," is a framework developed by the German Electrical and Electronic Manufacturers' Association (ZVEI) to support Industry 4.0 initiatives. Industry 4.0 is a holistic view of manufacturing enterprises, started in Germany, with many worldwide cooperative efforts including China, Japan, and India. RAMI 4.0 provides a structure and methods for modernizing manufacturing by guiding the development of smart factories that are more efficient, flexible, and responsive to market demands.

The framework is intended to identify standards and determine any necessary additions or amendments, and it is described in DIN SPEC 91345. RAMI 4.0 and the Industry 4.0 components are complementary, and the model is similar to the seven-layer ISO/OSI model used as a reference model for network protocols. It defines a service-oriented architecture (SOA) where application components communicate with each other through a protocol over a network, and the basic principles of SOA are independent of vendors, products, and technologies. The goal is to break down complex processes into manageable packages, including data privacy and IT security.

RAMI 4.0 consists of a three-dimensional coordinate system that describes all crucial aspects of Industry 4.0, breaking down complex interrelations into smaller and simpler clusters (Figure **44**). The first axis is the "Hierarchy Levels" axis, which is based on IEC 62264 and represents the different functionalities within factories or facilities. The second axis is the "Life Cycle Value Stream" axis, which represents the life cycle of facilities and products, based on IEC 62890. The third axis is the "Layers" axis, which describes the decomposition of a machine into its properties, structured layer by layer. RAMI 4.0 allows for step-by-step migration from the present into the world of Industry 4.0 and can be used to classify objects such as machines according to the model.

RAMI 4.0 architecture consists of the following main components:

- **Business:** This component covers the organization and processes of the smart factory.
- **Functional:** This component covers the functions of the physical assets in the smart factory.
- **Information:** This component covers the necessary data required for the operation of the smart factory.
- **Communication:** This component covers access to the information in the smart factory and the communication between different components.
- **Integration:** This component covers the transition from the real world to the digital world and the integration of different components in the smart factory.
- **Asset:** This component covers the physical things in the real world that make up the smart factory.

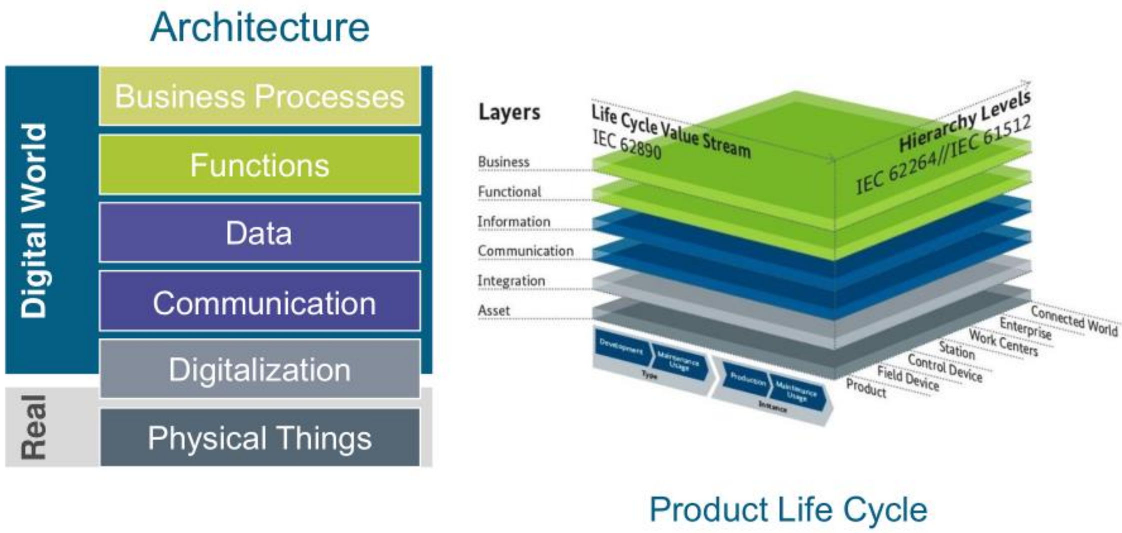


Figure 44: RAMI Architecture. © Plattform Industrie 4.0 and ZWEI. Graphs © Anna Salari

Mapping of some FAIRWork core components of the architecture to the RAMI Architecture:

- The **DAI-DSS User Interfaces** are mapped to the processes, as it covers the organization and processes.
- The **DAI-DSS AI Enrichment** are mapped to the functional layer. There the implementation of AI and non-AI based services are implemented.
- The **DAI-DSS Knowledge Base**, responsible for storing and providing data for decision processes, it is partly mapped to the data component. In FAIRWork, we have unstructured and structured data, models and knowledge. This is a difference to the RAMI initiate.
- The **DAI-DSS Configurator**, creating configuration files for microservices, is mapped to the Functions component.
- The **real-world part**, handling sensors, actuators, and real-world data, is mapped to the Physical Things component.

7 SUMMARY AND CONCLUSION

First, we defined and described the user requirements in detail. To do this, we used a model-based approach in this design process. This means that knowledge about a use case is externalized in the form of conceptual representations, using domain-specific modelling languages that are suitable and provide the required construct for representation and processing. The high-level scenarios are designed in a collaborative, interactive, and agile environment involving experts from different backgrounds. With this structured approach, the most important requirements are gathered in a few iterations.

After describing the application scenarios, the technical requirements of the scenarios were examined in terms of data availability and decision structure. The main challenges from the perspective of decision making were analysed. In the current production industry there is a need to make the current automated and hierarchical structured production processes more flexible. At the same time digitalization with AI support is seen as a key enabler for more energy efficient and resource efficient services, products or business models, by also enabling process optimization in the overall production process. Therefore, we describe in more detail the main technical challenges such as resource mapping and configuration, resource allocation, and resource selection aspects. These three challenges are highly relevant for making the process more flexible, adaptive, and resource efficient by using the relevant AI-based decision strategies in our complex distributed decision-making. At the end, the trustworthy AI aspect is a further key challenge to get AI accepted by the involved humans and utilize its potential.

In the next steps, our method - the well-known plan - do, check, act methodology is described. Therefore, this part gives an overview about relevant concepts for the research direction and implementation of such complex decision making by using AI services. In FAIRWork, AI is used in all our scenarios to automate processes or to make their processes more resource-efficient. Since humans are an important part of the overall decision process, trust in AI and human factors play an essential role and therefore these aspects are explained in detail. In this part, we show essential techniques to support humans with AI. This is because humans are not always able to comprehend complex and unstructured decision-making processes. This circumstance offers optimization potential by supporting human capabilities with AI technologies. The goal of using AI in a decision-making process is to speed up the decision-making. Traceability is very essential for establishing trust in the overall process.

Within the next part, the initial architecture of the project is presented. Based on the project goals and requirements, the high-level architecture of the platform has been outlined. This includes the main features description of the key components of the FAIRWork decision framework, while a detailed description of the components is given in D4.1. This also includes the technical implementation of the basic core services or application specific services.

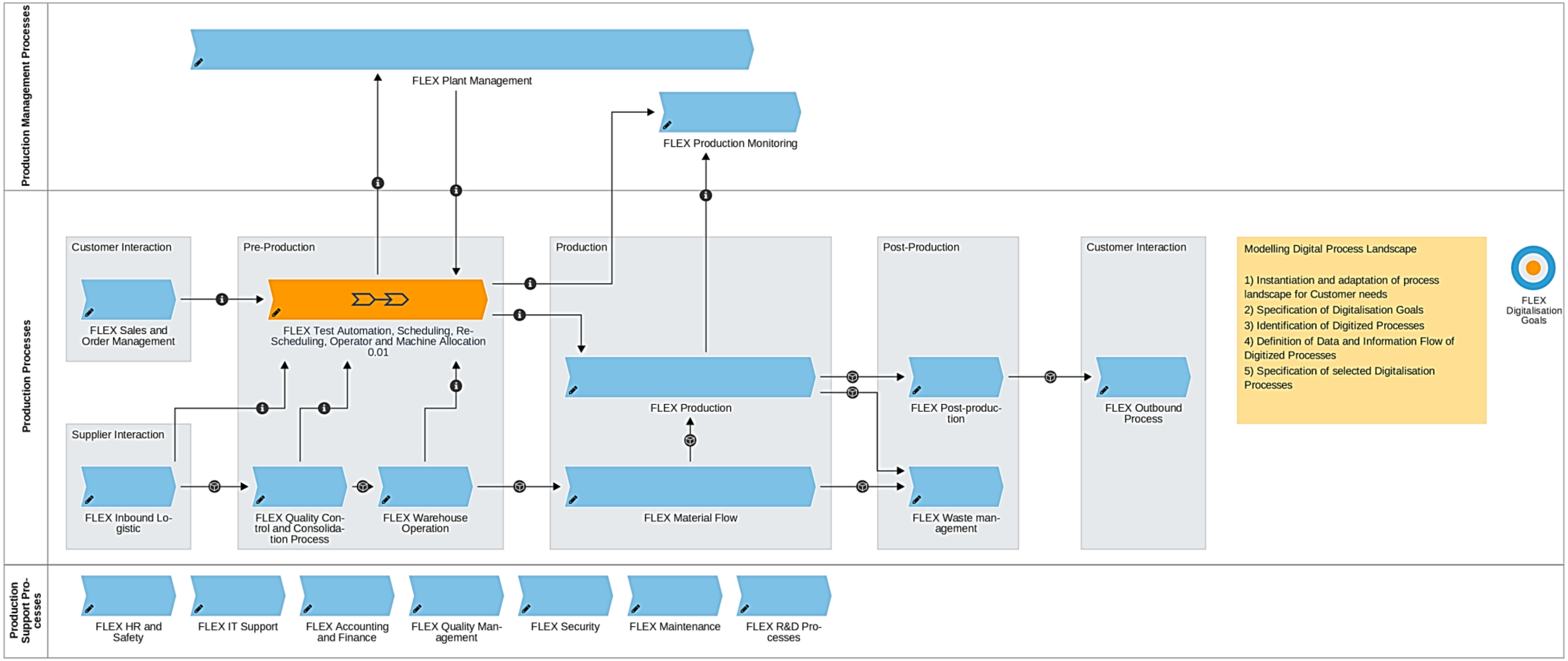
Finally, the initial outline of the FAIRWork architecture is compared with relevant other initiative and their architectures that are commonly used in the industry relevant domain, such as, Gaia-X, FIWARE, International Data Space, RAMI, and Industrial Internet initiative. There, we also point out the missing components for complex decision making in these initiatives.

8 REFERENCES

References are included as footnote within the text.

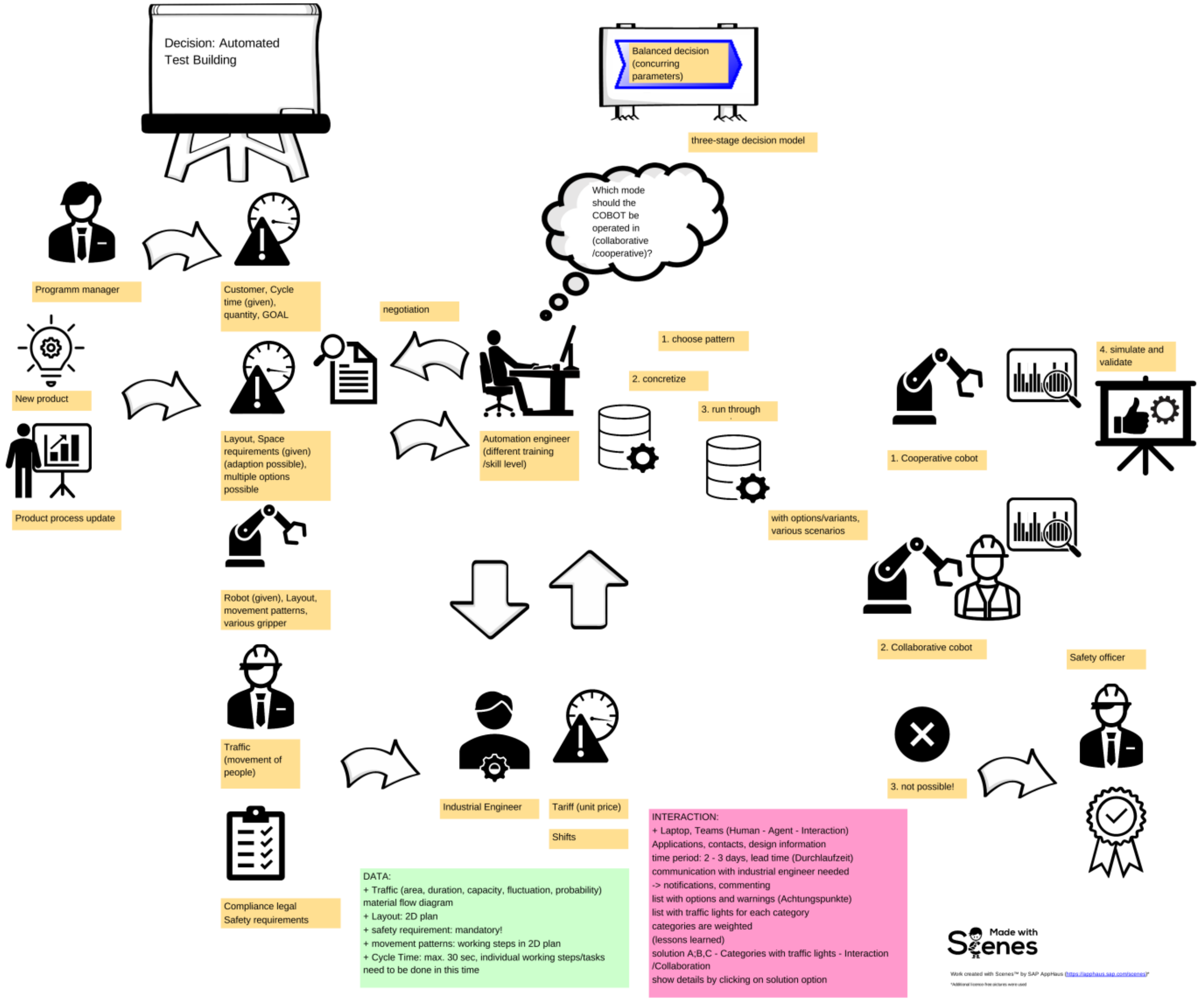
ANNEX A: LIST OF HIGH QUALITY FIGURES

Annex A.1 FLEX Process Map

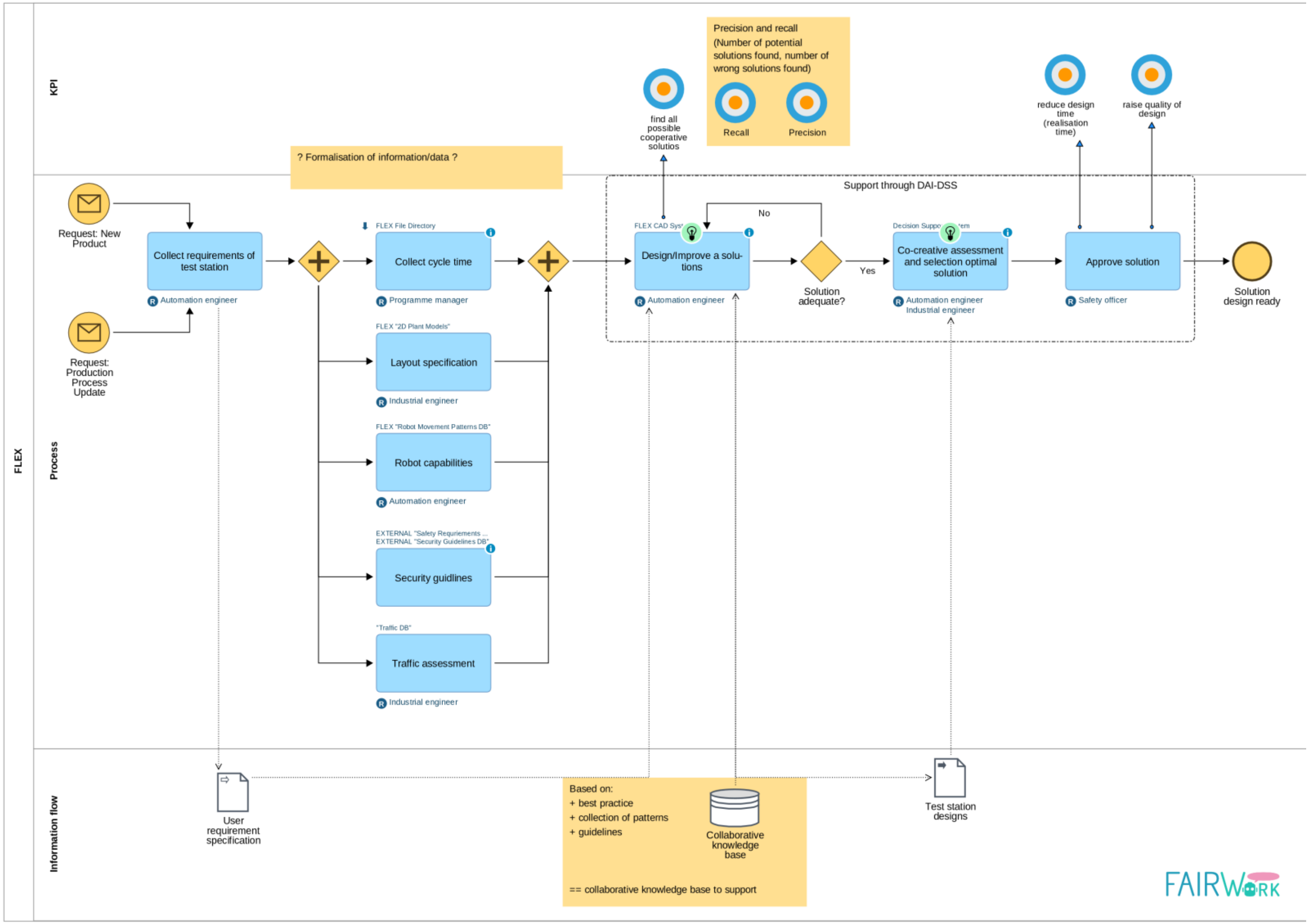


flex FAIRWORK

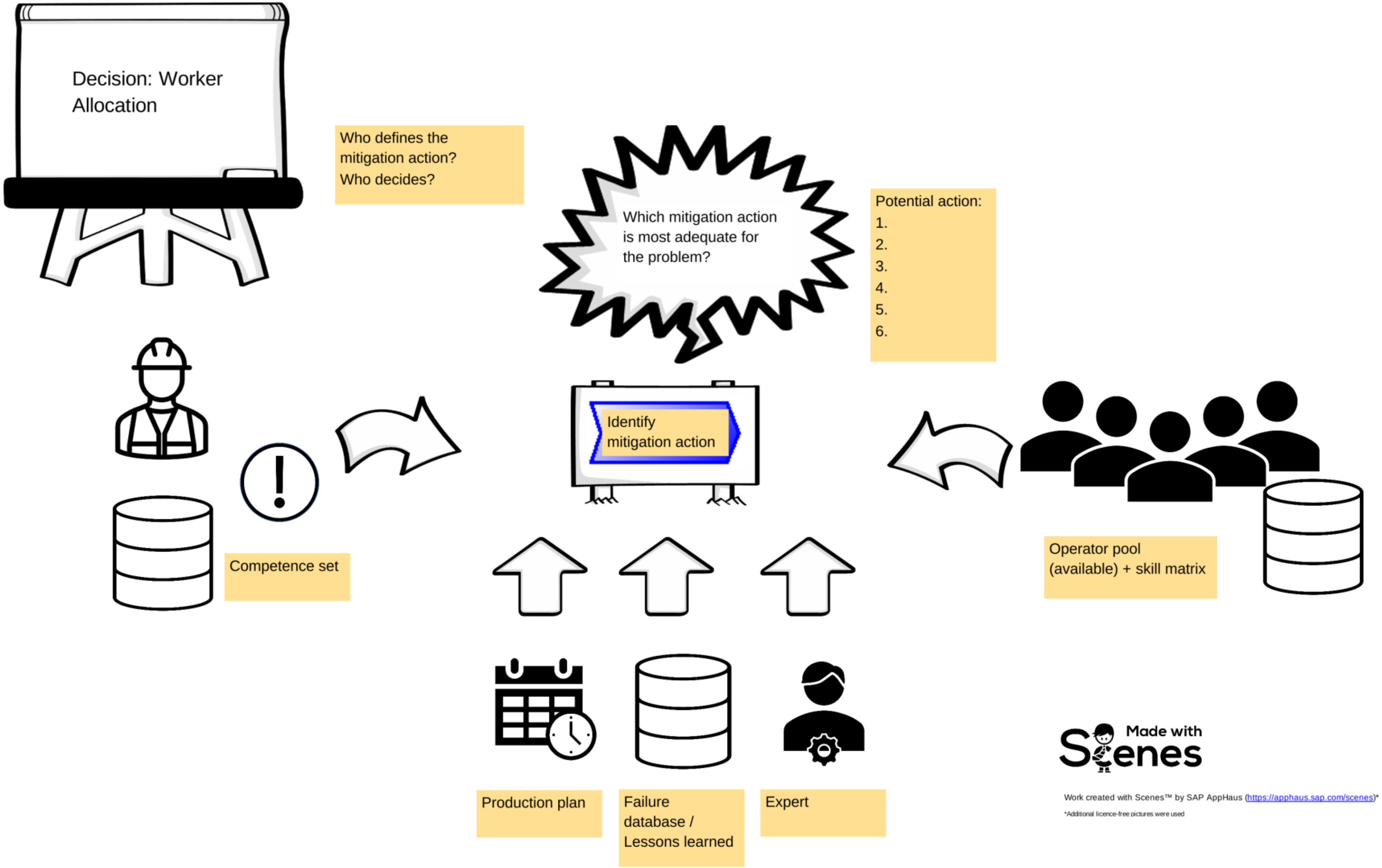
Annex A.2 FLEX Automated Test Building Scene



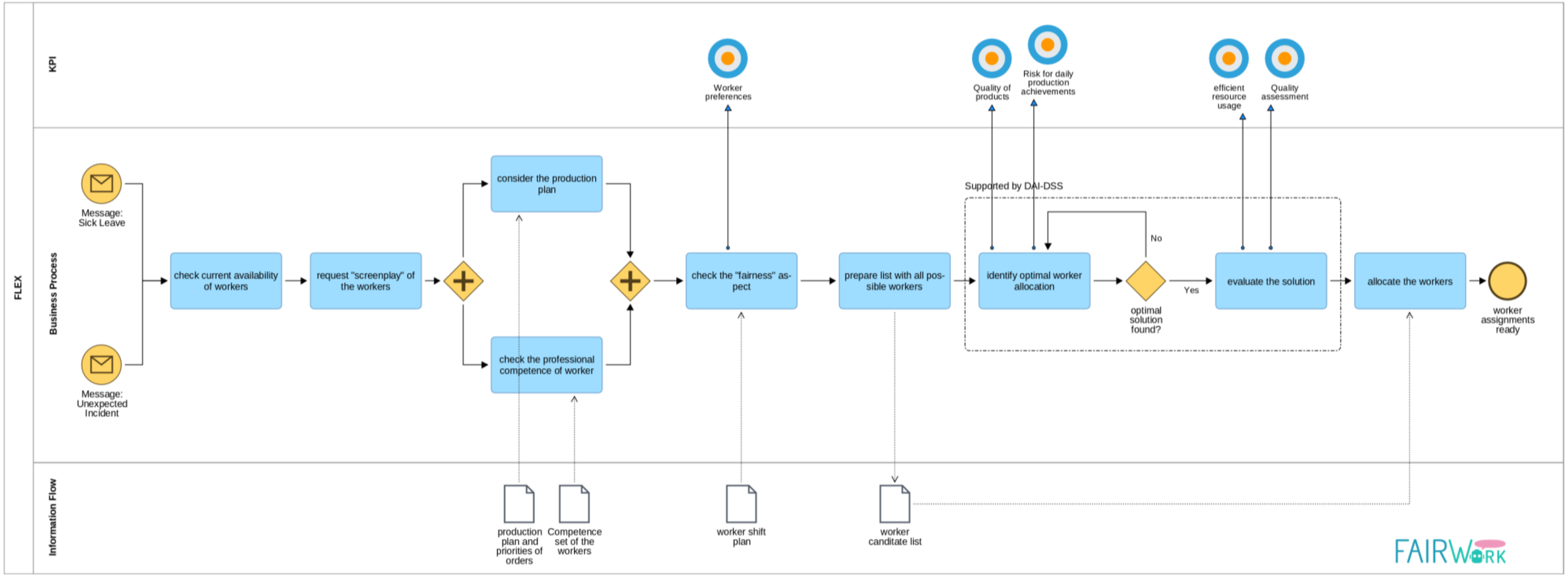
Annex A.3 FLEX Automated Test Building Process



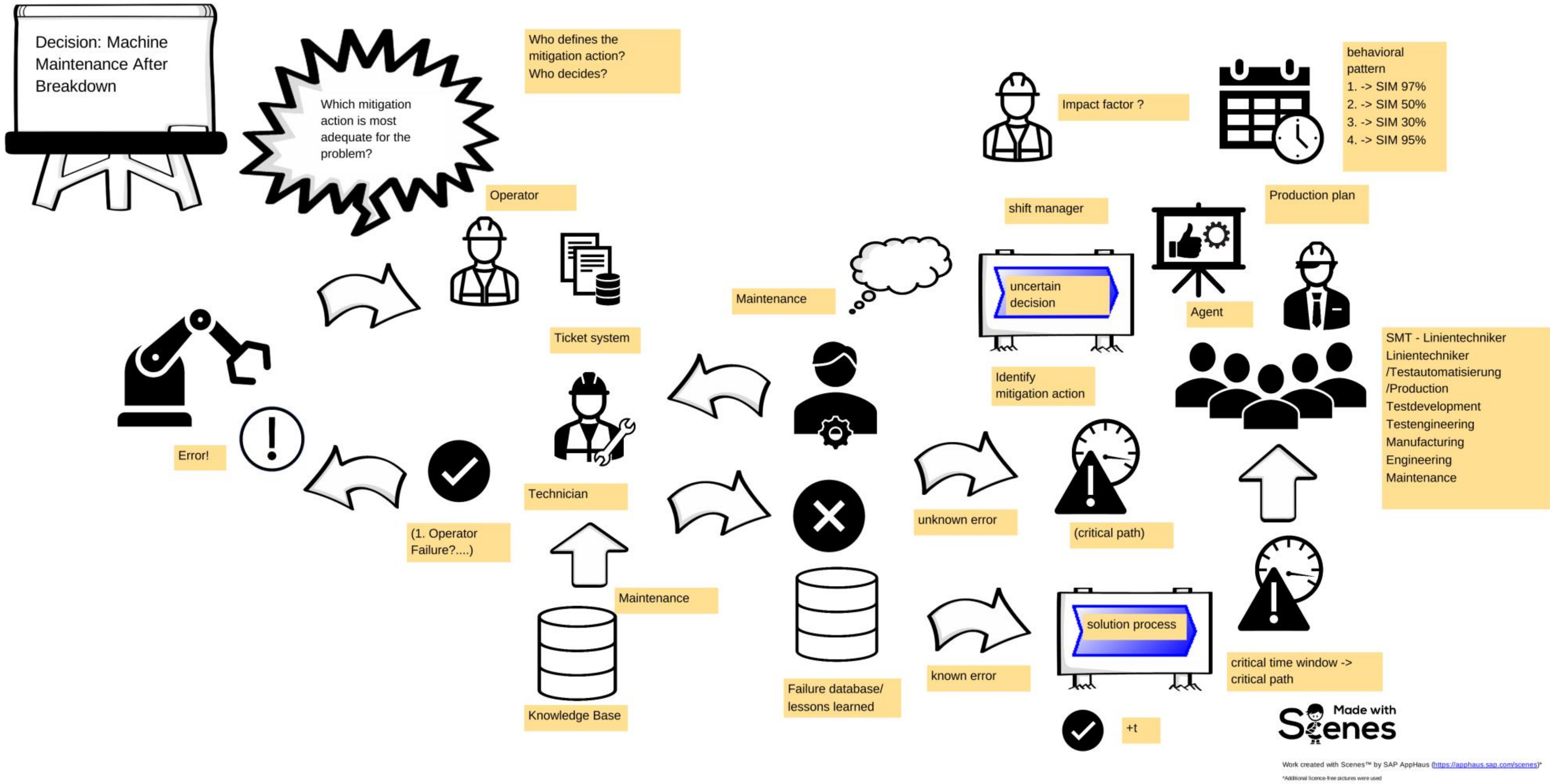
Annex A.4 FLEX Worker Allocation Scene



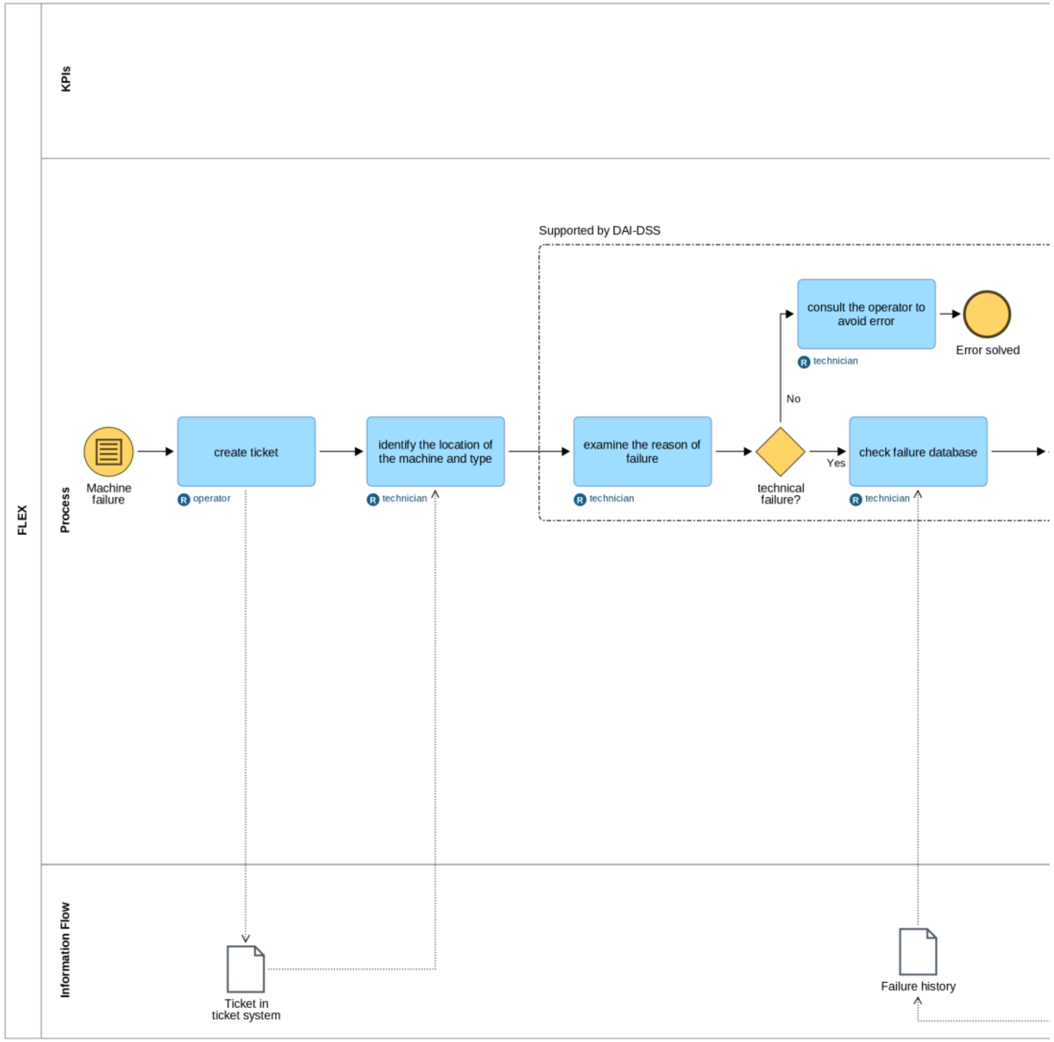
Annex A.5 FLEX Worker Allocation Process



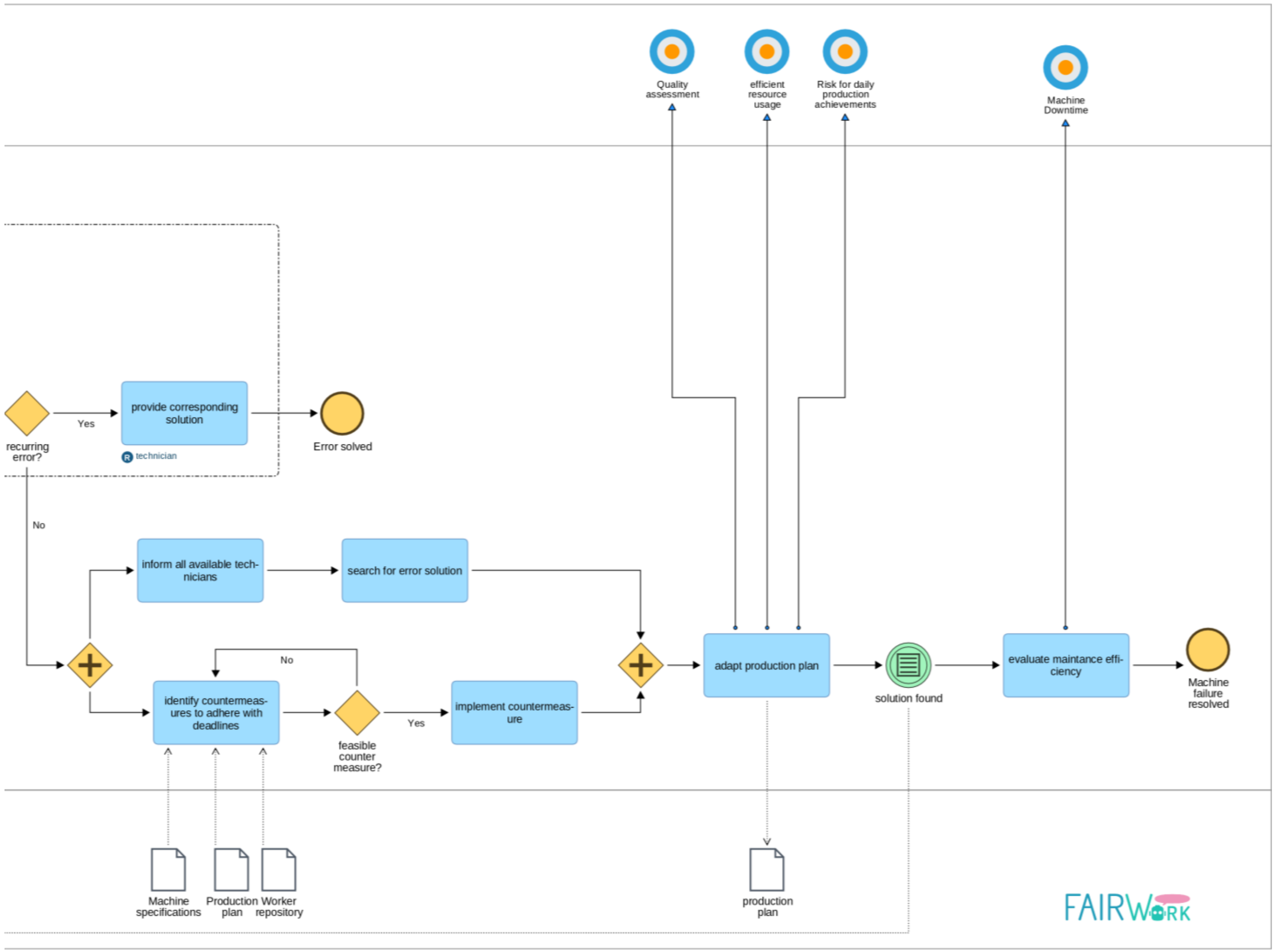
Annex A.6 FLEX Machine Maintenance after Breakdown Scene



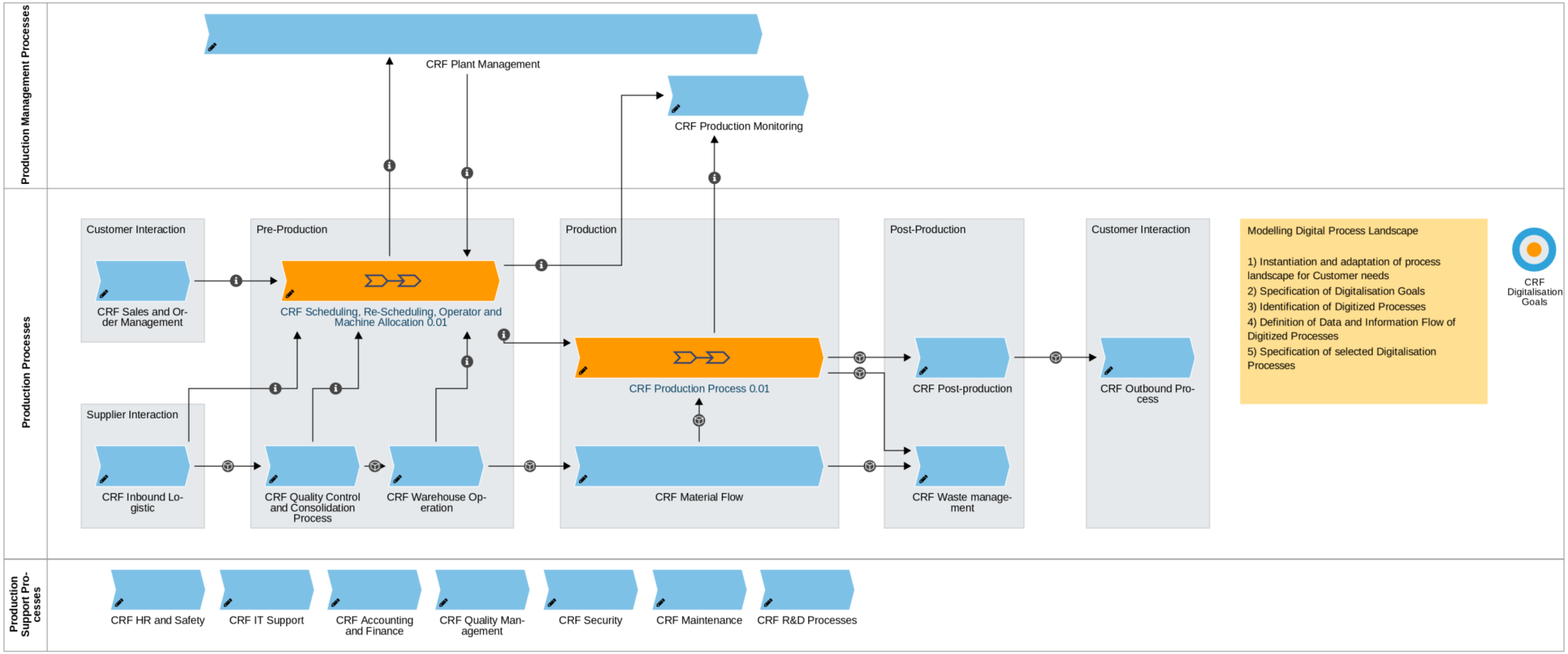
Annex A.7 FLEX Machine Maintenance after Breakdown Process (part 1)



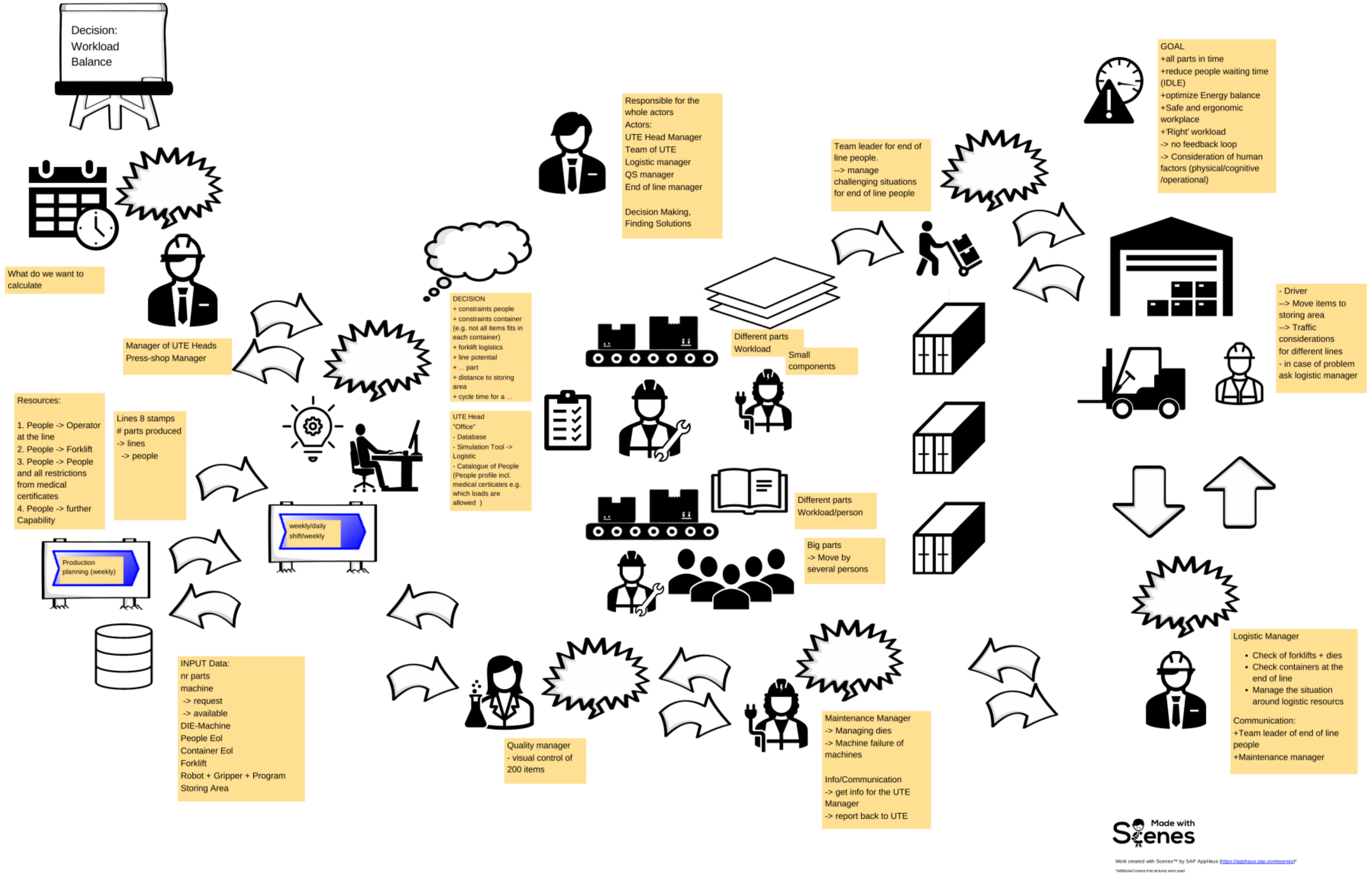
Annex A.8 FLEX Machine Maintenance after Breakdown Process (part 2)



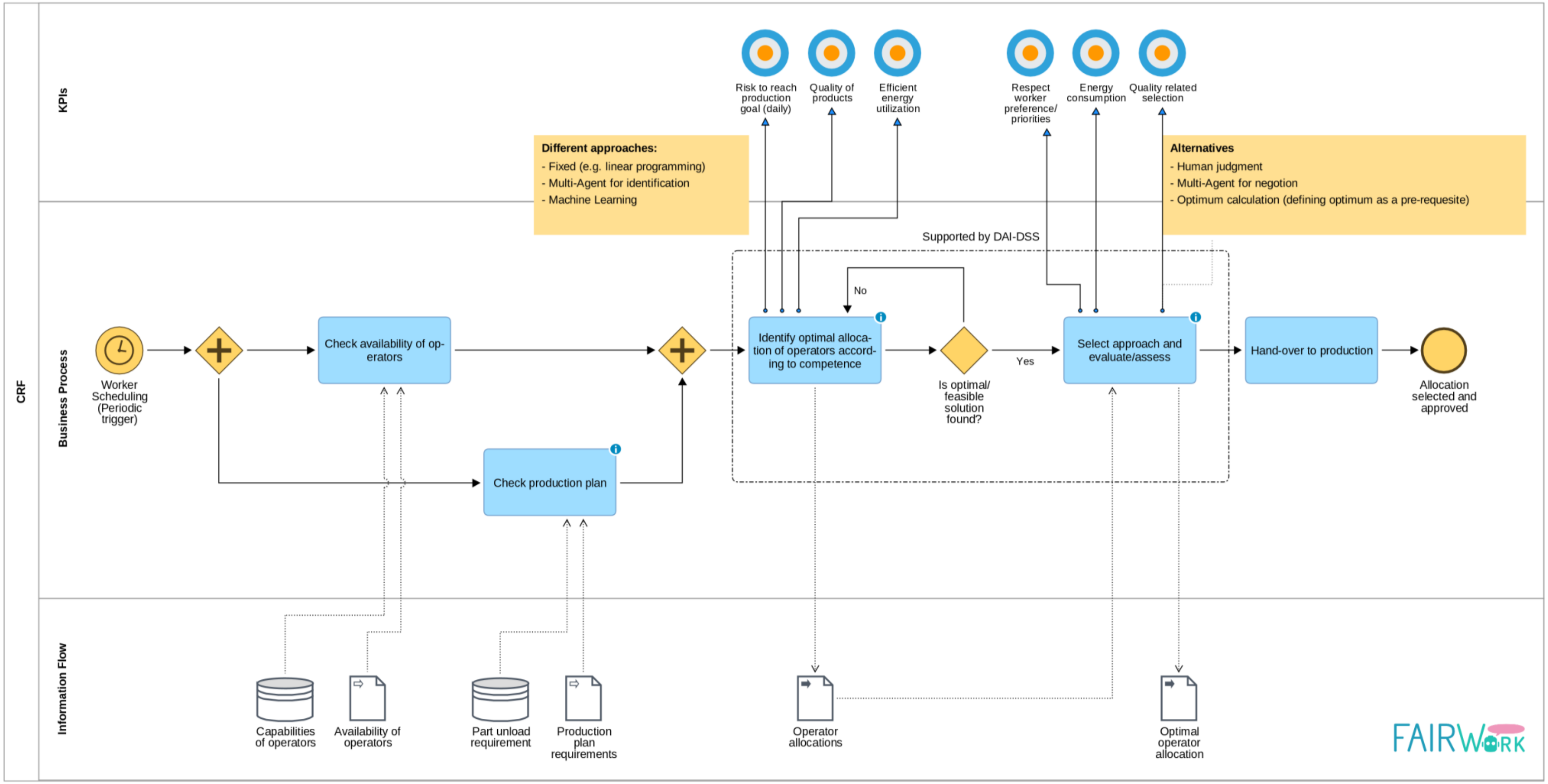
Annex A.9 CRF Process Landscape



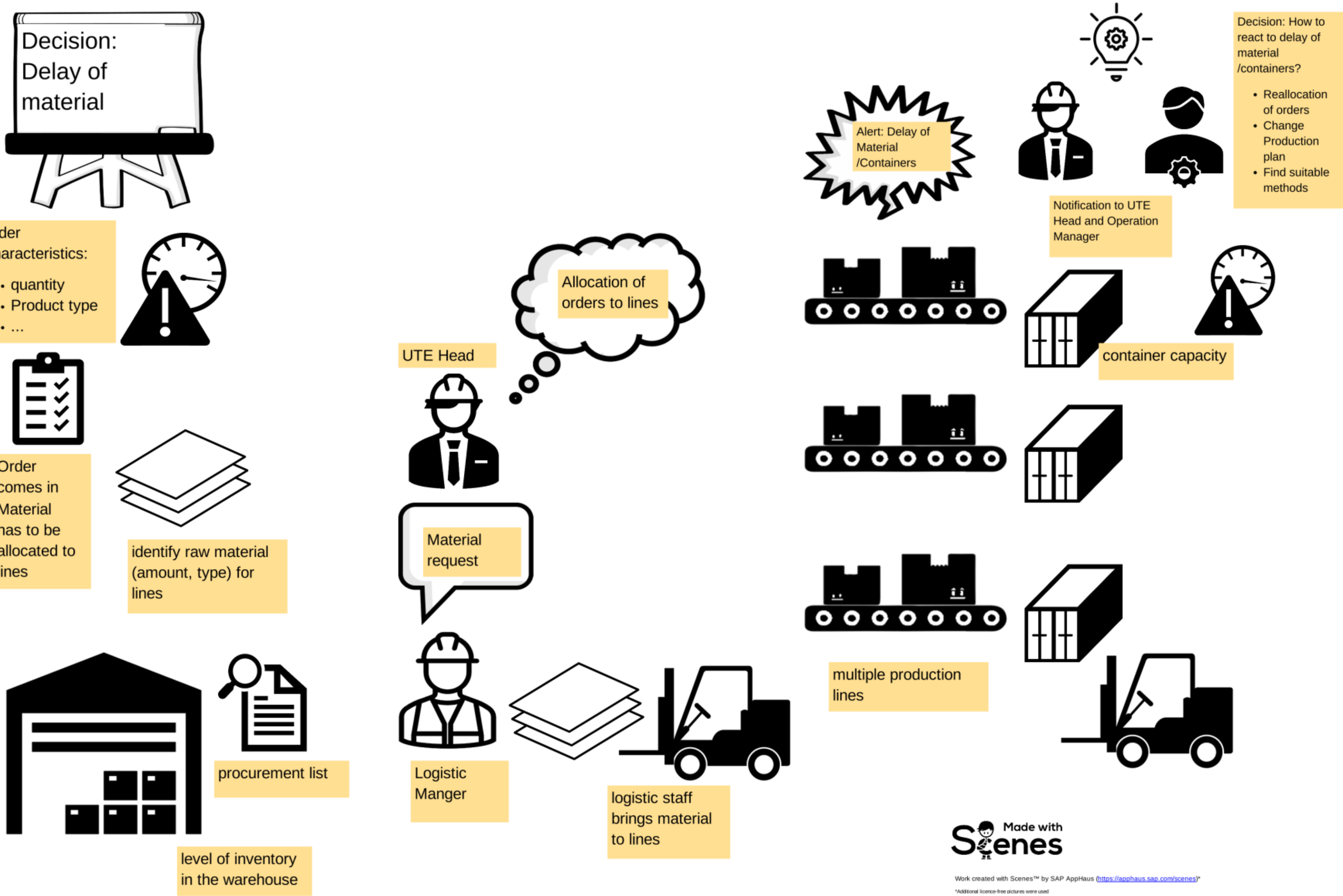
Annex A.10 CRF Workload balance Scene



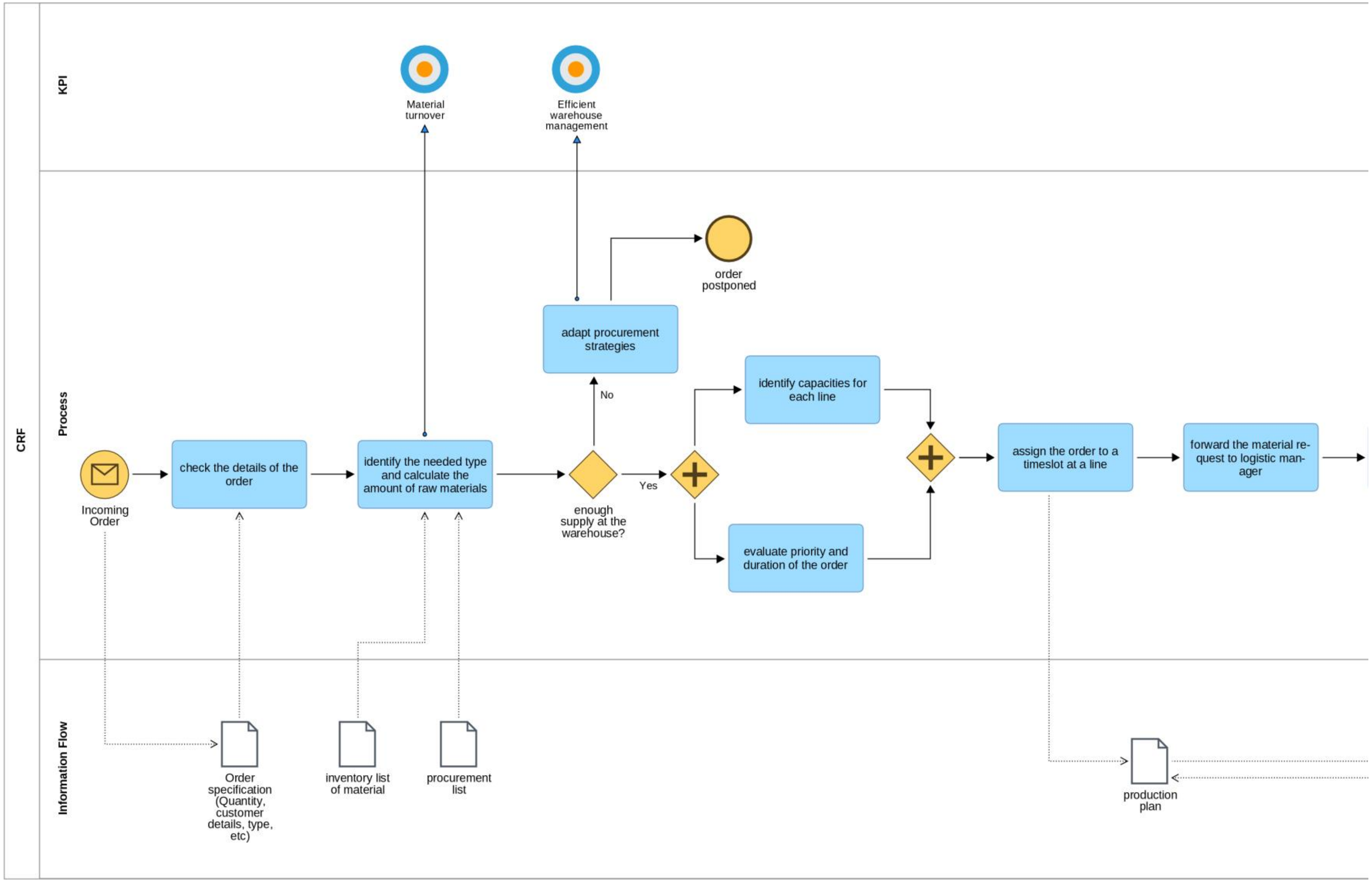
Annex A.11 CRF Workload balance Process



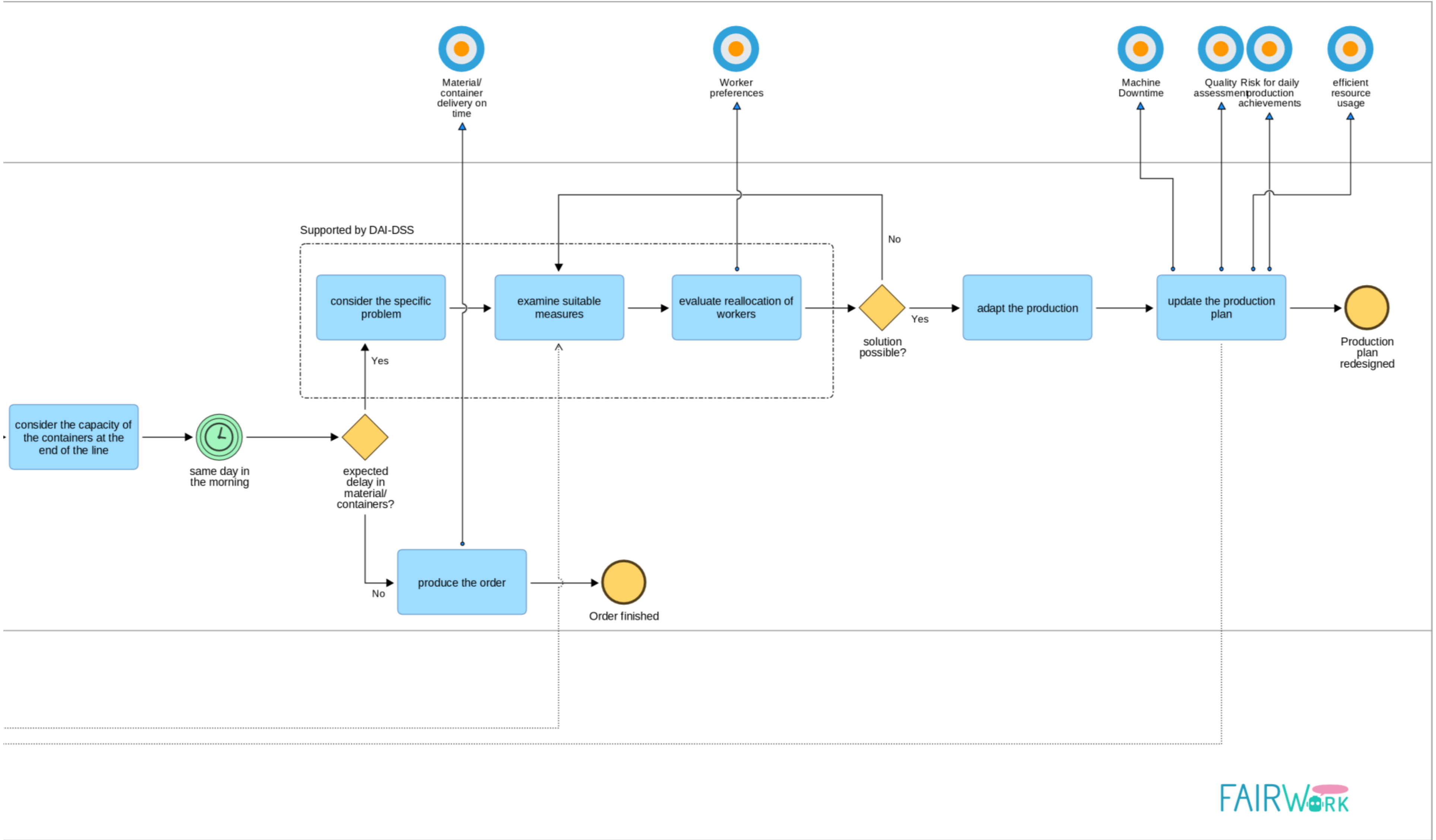
Annex A.12 CRF Delay of Material Scene



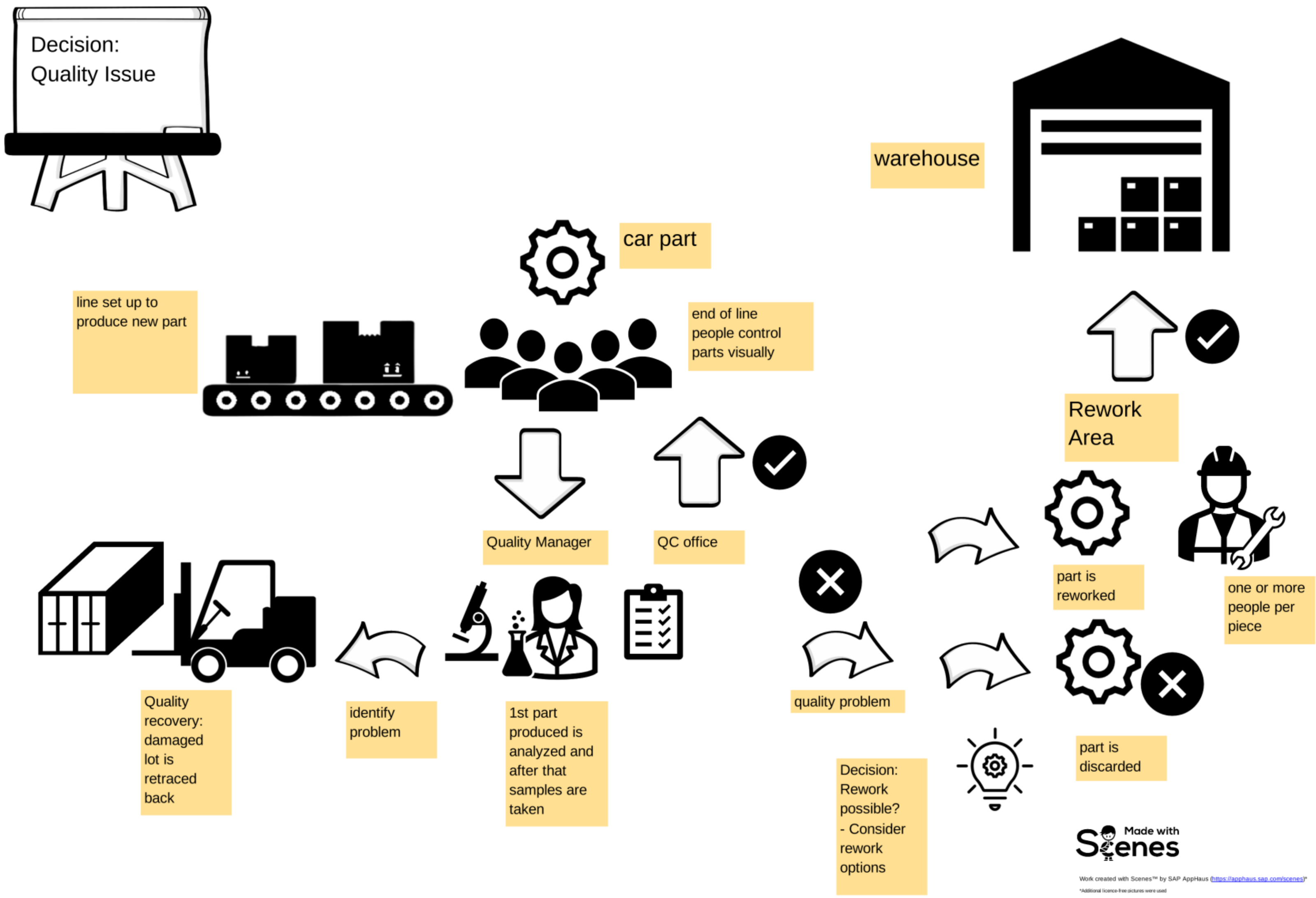
Annex A.13 CRF Delay of Material Process (part 1)



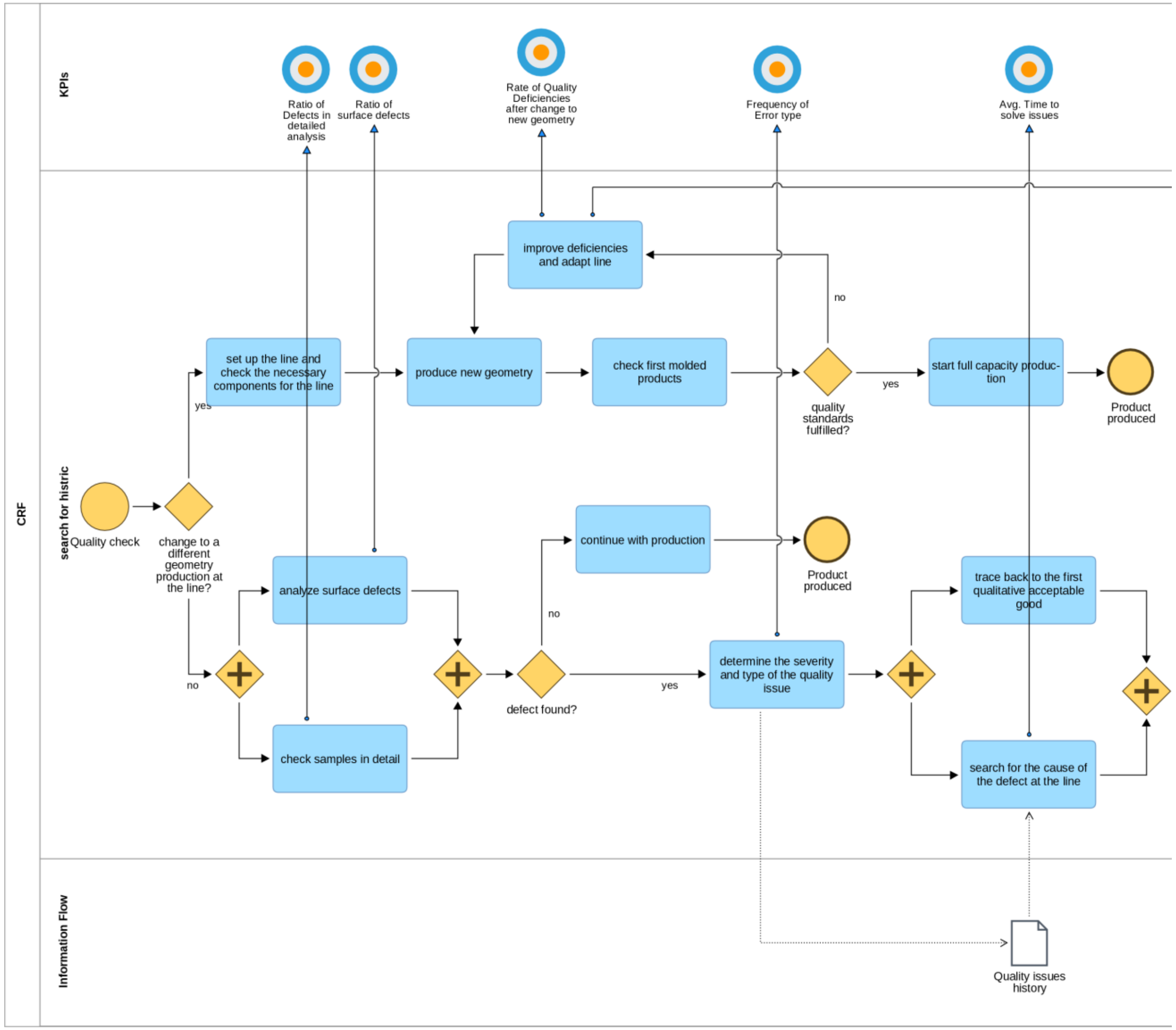
Annex A.14 CRF Delay of Material Process (part 2)



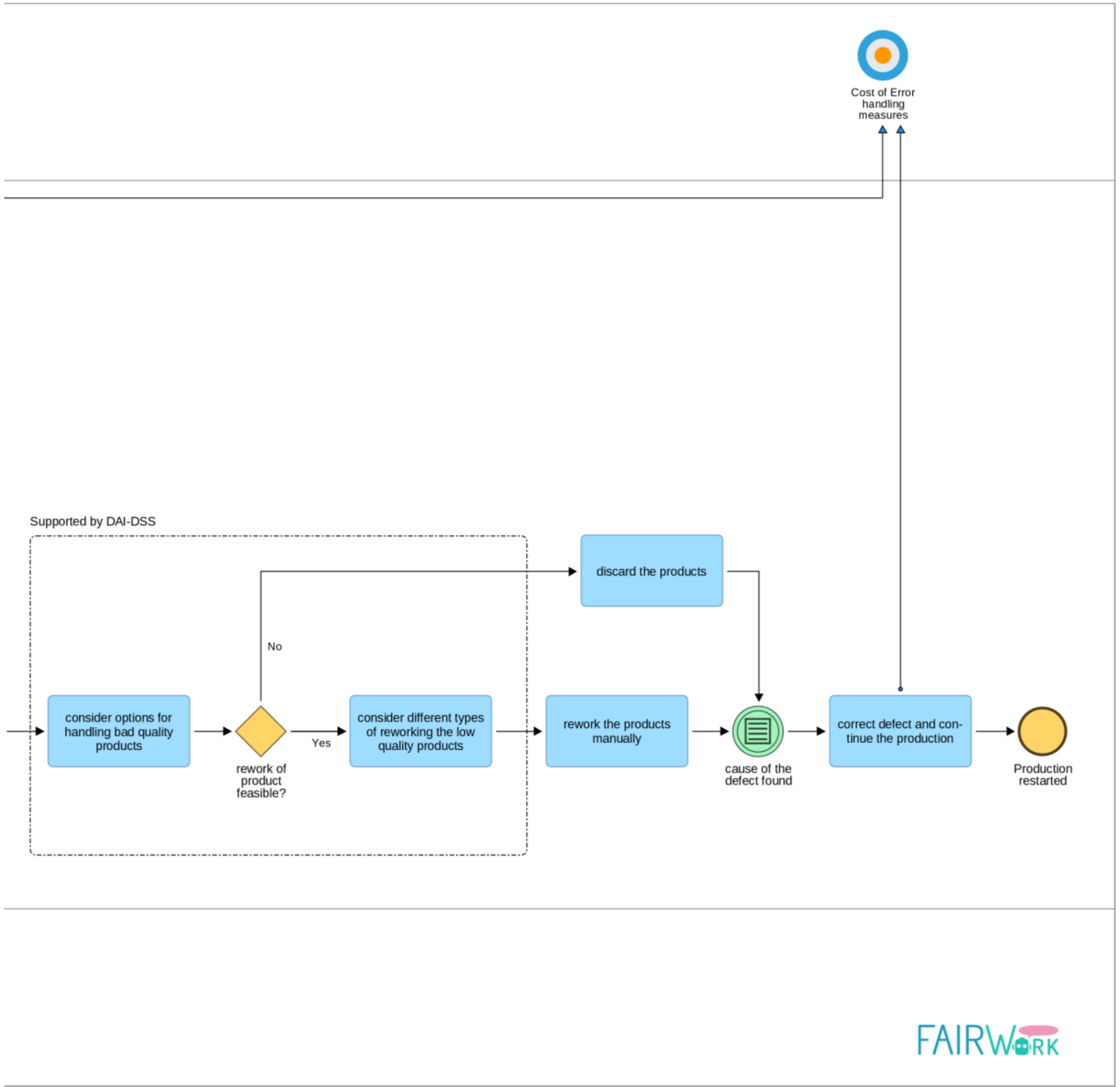
Annex A.15 CRF Quality Issue Scene



Annex A.16 CRF Quality Issue Process (part 1)



Annex A.17 CRF Quality Issue Process (part 2)



Annex A.18 FAIRWork High Level Architecture