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Using agents to perform Control and Configuration roles in Industry

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Summary

The advent of smart manufacturing and the exposure to a new generation of technological enablers have revolutionized the way how manufacturing processes are carried out. Cyber-Physical Production Systems (CPPS) are introduced as the main actors of this manufacturing shift. They are characterized for having high levels of communication and integration and for computational capabilities that led them to a certain level of autonomy. Despite the high expectations and vision of CPPS, it still remains an exploratory topic and several issues have to be clarified i.e. methodologies for its design and implementation.

Multi-Agent Systems (MAS), have been widely used by software engineers to solve traditional computing problems e.g. banking transactions. Because of their high levels of distribution and autonomous capabilities, MAS have been considered by the research community as a good solution to design and implement CPPS.

This work first introduces a background and literature review associated with the implementation of multi-agent manufacturing solutions in a product-driven manufacturing context. The research gap and aimed contribution of this deliverable is associated with the development of an integrated framework for agent-based process control, monitoring, optimal machine selection, and detailed data model specification. These ideas are later conceptually showcased in a real manufacturing product on a shop-floor with flexible transportation. The final section of this deliverable describes and presents conclusions, discussion, and future work ideas.

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Chapter 1

Introduction

With the advent of Industry 4.0, the manufacturing landscape is undergoing a significant transformation driven by the integration of advanced technologies such as the Internet of Things (IoT), artificial intelligence, and big data analytics. These technologies are enabling the development of intelligent, interconnected, and self-adaptive production systems, which are essential for manufacturing companies to remain competitive in the dynamic global market. The ability to rapidly adapt to changing production demands and requirements has become increasingly critical in this context.

A flexible and self-configuring production system is necessary to address this challenge, one that can autonomously adjust production processes, resource allocation, and machine configuration in real-time to optimize production efficiency, reduce downtime, and improve product quality. In recent years, the integration of multi-agent systems and machine learning techniques has emerged as a promising approach to develop such self-configuring production systems.

In this deliverable, we present a comprehensive framework for a self-configuring production system based on multi-agent systems and machine learning. The proposed framework encompasses several key components, including:

1. Data model specification: The data model is designed to represent the manufacturing domain and related entities, including products, processes, machines, and resources. This standardized representation enables effective communication and data exchange among the agents in the system.

2. Multi-agent-based negotiation: The multi-agent system enables decentralized decision-making by allowing individual agents to negotiate and cooperate to achieve their goals. The negotiation process ensures that resources and machines are optimally allocated to production tasks.

3. Machine monitoring: Continuous monitoring of machine performance and condition is crucial for identifying potential issues and ensuring timely maintenance or reconfiguration. The framework integrates machine monitoring techniques, such as sensors and data analytics, to provide real-time feedback and support adaptive decision-making.

4. Optimal machine selection: The framework employs machine learning algorithms to identify the most suitable machines for a given production task, considering factors such as capability, availability, and efficiency. This selection process ensures that production resources are utilized effectively and that product quality is maintained.

5. Machine configuration selection: To support the dynamic adaptation of the production system, the framework includes methods for selecting and implementing the most appropriate machine configurations based on current production requirements and constraints.

As a proof of concept, we apply the framework to the manufacturing of a manual expanding mandrel, a tool used in metalworking and woodworking to hold and expand a workpiece. The effectiveness of the framework is evaluated by its ability to optimize the manufacturing process, reduce downtime, and improve the quality of the final product. The results demonstrate the potential of the proposed framework to increase the flexibility and efficiency of production systems and provide a solid foundation for future research in this area.

The structure of this paper is organized as follows. Chapter 2 provides an overview of the background concepts and techniques relevant to this study, including intelligent product-driven manufacturing, semantics and data modeling, multi-agent systems in smart manufacturing, machine learning in smart manufacturing control, and cloud computing technologies. Chapter 3 presents a review of the literature related to intelligent products, machine learning for manufacturing control and configuration, agent-based solutions for manufacturing control and configuration, as well as cloud computing for manufacturing control and configuration. In Chapter 4, we introduce the proposed framework in detail, outlining the underlying assumptions, the data model, the negotiation strategy, and the methodologies for machine monitoring, configuration, and optimal machine selection. Chapter 5 demonstrates the applicability of our proposed framework through a case study, showcasing its practical implications and effectiveness. Finally, Chapter 6 summarizes our conclusions and discusses potential future work to further enhance and extend the proposed framework.

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Chapter 2

Background and Literature Review

In this section, we aim to provide a comprehensive overview of the key concepts that are relevant to the objective of this deliverable. Those represent an initial understanding to make autonomous manufacturing solutions. Also, we aim to provide a comprehensive analysis of the literature aligning relevant concepts for the control and configuration of manufacturing resources. This will be used to establish the rational and concrete motivation for this work.

2.1 Intelligent product-driven manufacturing

As manufacturing industry is moving from supplier-driven towards a customer-driven market, where customers are giving greater level of customization possibilities, changeover time has to be reduced, and re-routing of deliveries and handling of material can change, it is necessary to change traditional supervisory or centralized driven manufacturing design. Intelligent products can make the production planning and control more effective [1, 2] by providing explicit details of manufacturing design making them "intelligent". The definition of intelligent product was coined by M. McFarlane [3] in the early 2000s. It is described as a *physical and information based representation of an item for retail which:*

- Posses a unique identification.
- Is capable of communicating effectively.
- Can retain data about itself.
- Deploys a language to display its features.
- It is capable of making decisions.

Information from an intelligent product can have for example transportation details, guidelines for routing adjusting and the information and rules that represent the information of how the product has to be managed [2].

The concept of intelligent product has been explored in the literature under the umbrella of multi-agent systems i.e. product agent [4, 5, 6]. A product agent can communicate with other agents in the shop-floor (e.g, resources) to coordinate necessary manufacturing operations and generate self-organization. Products as a result of assembly operations are composed of parts i.e. part agents [7] or work piece agents [8] responsible for the process plan. In [9] an AGV agent (which contains the plan of the product) transports it to the needed resources. The information of the manufacturing information as a data base agent and decision making agent has been proposed to facilitate the information exchange [10]. The concept of order agent [11] encapsulates the information of one or more products that have to be manufactured.

2.2 Semantics and data modelling

New products resulting from product development processes have been represented principally by geometrical models. However, the growing need for customized products and shorter production times demands information, beyond geometrical aspects, to support production planning while retaining complete product information in the existing product lifecycle management (PLM) systems [12]. Given the characteristics of current PLM systems, information models have been proposed as an effective way of sharing this information in a machine-consumable representation. An information model is defined as "a representation of concepts, relationships, constraints, rules, and operations to specify data semantics for a chosen domain of discourse" [13]. Having a well-defined model provides a stable and shareable information structure for the studied domain [13].

Data exchange enables communication between the different actors in a digital manufacturing scenario. This communication is facilitated by the use of Well-defined data models that provide stable and organized structures for the exchange of information within a specific domain [13]. To date, several studies had proposed full or partial data models in the manufacturing field addressing different aspects, processes, or actors. For instance, a partial model for capability representation is proposed by [14] in which the minimum information requirements for atomic and complex capabilities with a focus on robotic handling tasks. In [15, 6], information models, as well as behavior models for a multi-agent scenario were defined to relate machines or devices to the production line. Similarly, [11] presented a more detailed relational database model for the configuration, control, and monitoring of a cloud-based manufacturing scenario. Other models were proposed with a higher level of abstraction or as support for complex activities such as supplier selection and order allocation presented by [10].

2.3 Multi-agent systems in smart manufacturing

Many advanced manufacturing schemes have already been proposed aiming to overcome the drawbacks of the current production lines, e.g., the flexible manufacturing system (FMS) and the agile manufacturing system (AMS). Among these schemes, the multi-agent system (MAS) is the most representative one, where the manufacturing resources are defined as intelligent agents that negotiate with each other to implement dynamic reconfiguration to achieve flexibility. Nowadays, the emerging cyber-physical system (CPS) presents a significant opportunity to implement smart manufacturing. The CPS can arm the MAS with emerging technologies (e.g., the Internet of Things (IoT), wireless sensor networks (WSN), big data, cloud computing, embedded systems, and mobile Internet). Multi-agent systems have been applied to the manufacturing domain a lot.

In the context of manufacturing control and configuration, agents may represent various entities within a production environment, such as machines, resources, products, or processes [6]. Each agent has its own set of capabilities, knowledge, and objectives, enabling them to function independently and adaptively in response to changes in the manufacturing system [4].

One of the primary advantages of agent-based solutions is the decentralization of decision-making processes, which allows for greater flexibility and adaptability in the face of dynamic production requirements [16]. Instead of relying on a centralized control system, agents can communicate

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and collaborate with each other to make decisions and optimize their actions based on local and global objectives [17]. This decentralized approach promotes better resource utilization, reduces system bottlenecks, and improves the overall efficiency of the production system [9]. Furthermore, agent-based solutions can be easily scaled to accommodate the growth or contraction of production systems, as new agents can be added or removed without disrupting the overall system functionality [15].

Several studies in the literature have explored the application of agent-based solutions for various aspects of manufacturing control and configuration [18, 11]. Some of these applications include resource allocation, machine scheduling, order processing, and production planning [19, 20]. In these studies, agents are typically designed to negotiate and cooperate in order to allocate resources, select machines, and schedule operations based on various criteria, such as minimizing production time, maximizing resource utilization, or minimizing production costs [11, 7]. Additionally, the incorporation of machine learning techniques, such as reinforcement learning and artificial neural networks, further enhances the adaptability and intelligence of these agent-based solutions [10, 8]. As a result, agent-based solutions for manufacturing control and configuration hold great promise for creating flexible, efficient, and adaptive production systems capable of meeting the demands of the dynamic global market [21, 22].

2.4 Machine learning in smart manufacturing control

There is an increasing need for an intelligent control for smart manufacturing to a quick adaptation of manufacturing system to changes/disturbances. Researchers have addressed this need through the implementation of machine learning techniques along with the system [23]. These machine learning enabled trained systems are capable of retraining itself with respect to new information from the shop-floor, purchase demands and market conditions and adapt itself. These adaptive system requires less physical effort to adjust itself to new requirements.

Machine learning techniques, such as reinforcement learning and neural networks, are increasingly applied in agent-based manufacturing control to enhance scheduling algorithms' real-time response, generalizability, and decision-making abilities. These techniques enable agents to adapt to the specific aspects of the problem, handle high-dimensional data, and model human behavior. For instance, AMAM framework [24] uses reinforcement learning to help agents learn and adjust their behavior in finding solutions to combinatorial optimization problems. In addition, reinforcement learning optimizes reward functions and guides multiple AI schedulers in real-time scheduling for a smart factory setting [25].

Multi-agent reinforcement learning is applied to learn the decision-making policy of each agent and cooperation between job agents in scheduling algorithms for solving job scheduling problems in a resource preemption environment [26]. Reinforcement learning could also be used to model human behavior in the creation of Digital Twins with foresight, enabling situational selection of production control agents. This approach allows for circumstantial control strategies that can outperform traditional approaches and presents strategies for improved situational agent selection [27].

Innovative neural networks are used for each manufacturing unit to schedule operations with real-time sensor data in a smart factory setting, allowing effective handling of high-dimensional data and collaboration between AI schedulers for improved scheduling performance [25]. Moreover, some proposed methodologies, such as the dynamic scheduling problem in cloud manufacturing, utilize both neural networks and reinforcement learning to produce novel agent-based solutions, which are trained using multi-agent reinforcement learning and graph convolution networks for improved real-time response and generalizability [16]. Thus, machine learning techniques offer promising

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opportunities for agent-based manufacturing control, enabling efficient scheduling and optimization in manufacturing environments.

2.5 Cloud computing technologies

In the recent research we observe an increasing trend of incorporating cloud technologies in manufacturing applications. There have been agent architectures that such manufacturing applications through agent integration [7]. These kinds of architecture are being integrated with cloud services for manufacturing control and configuration purpose. The PROSA architecture [7] was extended with a goal based execution model that employed a BDI semantics and business process modelling to make it more easily adaptable to cloud infrastructure through partial, functional blocks for resources. In manufacturing application, task scheduling is a case where the cloud computing is adopted [16] through agents supported with reinforcement learning. Another case of adoption is seen in healthcare sector [28] where agents coupled with cloud technologies support management model for ECG monitoring. The cloud here serves as a means of connecting the person agents (a network of sensors) to the ECG network (where other agents are present).

To solve the scheduling problem in a resource constraint environment, multi-agent reinforcement learning is used to prioritise and schedule tasks [26]. A cloud based approach be integrated here to make data driven decision-making where each job can be considered an agent. The information on each job can be hosted on the cloud and RL can be used to control all agents in a cooperative manner. Cloud technology in this manner can also support digital twin to develop foresight for job shop scheduling/ production control [27].

A summary of the literature revised in this section, categorizing agents which are being used, the concept of intelligent products, machine learning techniques, use of cloud computing, and specification of data models is presented in Table 2.1.

Table 2.1: Summary of references considered

Ref	Agents	Intelligent product	Machine learning	Cloud computing	Data models
[14], 2017	Component, production management capability management	Component agents	NA	NA	Partial. Capability representation
[29], 2018	Coordinator, workstation, workstation executor	YES	NA	NA	NA
[24], 2019	Metaheuristic	Meta-heuristic agents	Reinforcement Learning	NA	NA
[10], 2018	Database, supplier, decision maker, order allocator	Database agent, decision maker agent	NA	NA	Partial. Mathematical model of order allocation
[30], 2019	NA	NA	NA	NA	NA
[18], 2021	Supplier, Production, Company, Customer	NA	NA	NA	NA
[31], 2021	Task, Printer, Master	NA	Artificial Neural Network	Orchestration	NA
[25], 2021	Scheduler	NA	Reinforcement Learning	Monitoring, data analysis and proces planning	NA
[32], 2021	Generic	NA	Yes	Server	NA
[19], 2018	Feature, Part, Machine	NA	NA	Virtual cells formation	NA
[15], 2019	Machine, Transport, Process	NA	NA	Storage, HMI and MES	Partial. Petri net behavior model
[33], 2021	Self-organizing, man, machine, material, mathod, Environment	Shared resources	NA	Pool of services, storage and communication	NA
[17], 2017	Station level: Station control, station monitoring, manufacturing resource. Shop level: shop management, shop monitoring, command agent	NA	NA	Data servers for storing models and knowledge	NA
[4], 2019	Initializing, Product, Knowledge, Decision maker, Communication manager, Resource	Product agent	NA	NA	NA

Continuation of Table 2.1					
Ref	Agents	Intelligent product	Machine learning	Cloud computing	Data models
[11], 2018	Resource, order, supervisor, interface for optimization	Order Agent	NA	Data base and optimization engine	Yes. Relational data base comprising resource, operation, product and order.
[34], 2019	Product, resource, remote monitoring, introspector	NA	NA	–	NA
[9], 2021	Resource, order, digital twin	AGV agent with product info	Yes	Digital twin shopfloor	NA
[5], 2018	Product, resource, schedule, batch,	Product agent	NA	NA	NA
[7], 2018	Part, resource, order, staff	Part Agent	NA	NA	Partial. Function blocks for resource control
[16], 2022	task	NA	Reinforcement Learning	YES	NA
[28], 2021	Fog node, master, personal, master personal	Personal Agent	Yes	YES	NA
[26], 2022	Job	NA	Reinformcement Learning	NA	NA
[27], 2021	Decision making instances	NA	Reinforcement Learning	NA	NA
[20], 2016	Smart machine	NA	NA	Services of agents are wrapped as cloud manufacturing services	Partial. Smart machine agent model with no attributes
[6], 2017	Suggestion, products, machining, conveying	Product agent	NA	For cloud control feedback: Schedulling from MES, SCADA	Yes. Ontology for a machining agent. Also, high level model of the product line.
[22], 2018	Robotic arms, sealing machine, automatic storage and retrieval, conveyor belt, product	NA	NA	Interaction between cloud and clients, Cloud and shop-floor entities Big-data	NA
[21], 2017	Product, Machine	YES	NA	Storage and big data	NA
[8], 2019	Machine, Workpiece, Transporter	Work piece agent	Artificial Neural Network	NA	NA
[35], 2018	Logical segment, crossroad, AGvs agent avatar, AGV agent	NA	NA	NA	NA
End of Table					

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2.6 Contribution of this work

In line with the literature review presented, the focus of this work considers the next research trends and challenges.

- Manufacturing process control: A multi-agent based infrastructure will support the distributed decision making and negotiation of resources in the shop-floor. An intelligent product driven methodology will be used as baseline to showcase products of batch size one.
- Machine product-driven configuration parameters: Configuration parameters are driven by product specification and generic capabilities of the machines. This has been generally elusive when considering manufacturing control applications since they are mostly focus on the orchestration and control process.
- Monitoring and diagnosis of the current status of machines to determine their remaining useful life. Monitoring variables can be used as a decisive decision-making entity in the control and coordination process. Machine learning mechanisms can provide further insights of machine status.
- Detailed data model and specifications for manufacturing products and resources as well as their relationships.

Overall the previous four items will constitute the target for the development of the current framework, which will be detailed in next chapter of the deliverable.

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Chapter 3

Framework

Current chapter presents implementation details of the framework. It covers specific assumptions for its development, the description of the data model, the negotiation strategy, and methodologies for machine monitoring, configuration and optimal machine selection.

3.1 Assumptions

The developed framework is designed to optimize the production of single-component products. To achieve this, certain assumptions have been made about the process:

- Product characteristics – All products are assumed to be single-component with a predefined set of tasks based on their characteristics. This allows for a streamlined and efficient production process.
- Machines and tools – All machines are stationary and have their own set of tools, ensuring consistent quality and reducing the need for additional equipment. Jigs and fixtures for the machining process are not within the scope of the work.
- Batch size – The assumption of batch size one production means that each product is manufactured individually, resulting in a more specialized and customized production process.
- Process flow – The process flow is composed of one or more sequential tasks, with each product following a predetermined sequence of tasks based on its characteristics. This ensures a consistent and efficient production process.
- Intelligent products – All products are considered intelligent, enabling them to interact with the production process and provide feedback on their progress, allowing for continuous process improvement.
- Transport units – All transport units (AGVs) have the same capabilities and are stored in the same place, allowing for efficient material handling and reducing the need for additional equipment.
- Process planning – The framework assumes that the manufacturing process is already planned and that there is no process planning stage required. This allows for a more streamlined and efficient production process.

In summary, the developed manufacturing framework optimizes the production of single-component products by assuming consistent product characteristics, specialized machines and tools, batch size one production, a predetermined process flow, intelligent products, efficient material handling, and no process planning stage. These assumptions lead to a more streamlined and efficient production process, resulting in high-quality single-component products.

3.2 Data model specification

The framework described in this document considers the product-process-resource dynamic, in which the product, through the tasks required for its manufacturing, demands specific capabilities that the skills provided by the resources can realize [36].

In this sense, the first step was to devise a data model that contains the minimum information required to describe the product, tasks, and resource characteristics, support the machine monitoring, and facilitate resource reconfiguration. This data model was defined using generic entities to simplify its adaptation by the user and its extension to different manufacturing scenarios.

A quick glimpse of the proposed approach is shown in Fig. 3.1, which depicts two models, one representing the product and its requirements and the other describing the available resources, linked through an entity, called 'Template'. All entities considered in this approach are identified by 'ID' and 'name' to facilitate their traceability. A status attribute was also included for the dominant entities to report their progress within the manufacturing process. The entities and the links between them are described in the following.

Product

This entity aims to identify the product and highlight its main manufacturing characteristics in an elementary way.

Besides the product identification attributes and status, the attribute 'properties' stores a list of product characteristics relevant to its manufacture that will not change throughout the product realization; for instance, its material, its color, the product variant, the estimated cycle time, and the size and weight of the final product, among others. On the other hand, the attribute 'trace' keeps a set of product properties whose value can change during its realization, such as its current location, current process, and remaining processing time, to cite a few. Both attributes, 'properties' and 'trace' are modeled as a list of elements derived from the entity 'Property'.

Additionally, every product requires a set of activities for its manufacturing, each modeled by the Task entity.

Task

The entity 'Task' describes every activity required for manufacturing the product. Each instance requires identification attributes and the status, which is independent of the Product status, for progress tracking. 'SeqOrder' attribute specifies the order in which the task must be carried out. The attribute 'estimatedProcessingTime' is assigned at task creation according to statistical or historical data, providing a forecasted duration for this specific task. The 'Trace' attribute is used in the same fashion as in the 'Product' entity.

The task's characteristics demand the resource that would execute it to meet several capabilities described using the corresponding entity.

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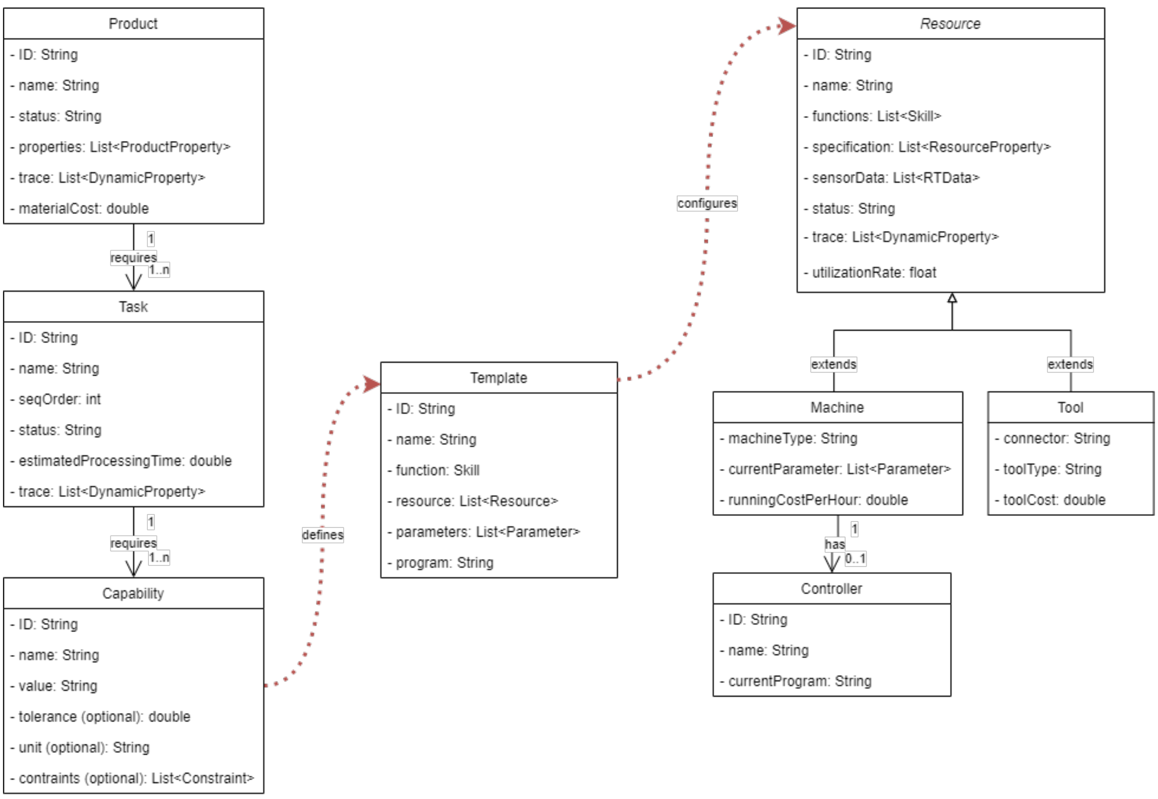

Figure 3.1: Proposed model for resource reconfiguration based on product requirements

Capability

This entity captures the specific requirements to execute a task. 'ID' and 'name' attributes are used for identification, while the 'value', 'tolerance', and 'unit' can be used to specify quantitative and qualitative capabilities. Also, the constraints of each capability can be represented by a list of elements derived from 'Property', which will be described later.

Resource

Similar to the products, the resources are represented in a synthetic and generic manner, which is why the abstract entity 'Resource' was defined. This abstract entity can be of different types, a machine or a tool in this case. Still, it can extend to cover other types of resources, such as measuring devices, human operators, or other devices. If the resource is a *Machine*, its type and parameters are required; if it is a *Tool*, its type and connector can be specified, all besides the attributes inherited from the 'Resource' entity. A 'Controler' entity was created to complement the 'Machine'; the NC program currently running on the controller can be specified as an attribute.

Independent of its type, a resource would have identification and status attributes. It will also possess fixed characteristics for resource selection such as 'specifications', a list of properties, and 'functions', represented by the entity 'Skill'. The dynamic characteristics such as 'sensorData', modeled by the 'RTData' entity, and 'trace', already described for previous entities, allow resource monitoring and configuration.

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Skill

The counterpart of a capability for a resource is the skill. This entity represents each function provided by the resource to execute a manufacturing activity. Besides identification attributes, a skill requires a type specification to categorize it easily (See Fig. 3.2 a). These categories are listed in the 'SkillType' enumeration; initially, two categories (transport, transform) are proposed but more can be added by the user or by applying an existing taxonomy.

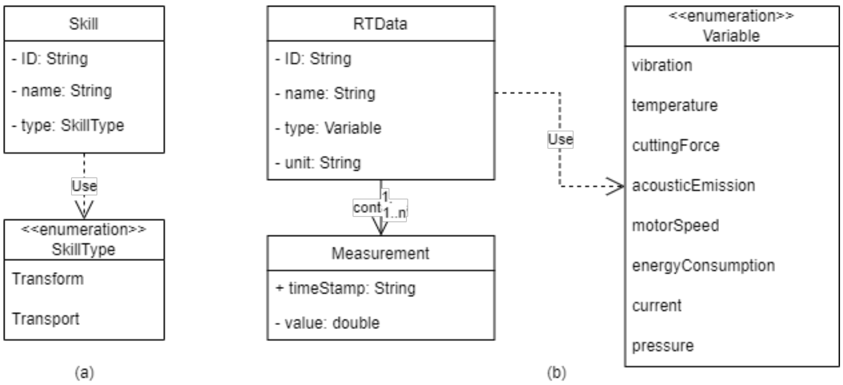

Figure 3.2: Skill and RTData entities

RTData

The 'RTData' entity supports resource monitoring by representing all measured values in a structured way and establishing their relationship with the corresponding resource (Fig. 3.2 b). Each instance of this entity refers to the type of the variable being measured, its unit, and can store a set of 'Measurements' with a timestamp and value. Predefined variables are listed in an enumeration and more can be added, depending on the manufacturing scenario.

Template

To relate a task to a resource, an entity 'Template' was defined to support resource reconfiguration by matching a capability with a suitable resource and setting the corresponding parameters, programs, and elements to it. For these purposes, a template contains the function being addressed, modeled by the 'Skill' entity; the resource or resources required to realize the capability, with a list of 'Resource'; the required parameters according to the product characteristics; and the corresponding NC program, if applicable.

The 'Template' was the essential entity in the proposed approach since it provides a space to portray the different roles of the resources depending on the product characteristics, and how predefined templates can configure the production system accordingly in an effective manner.

Property

Finally, the abstract entity 'Property' was created as the root of different types of elements that intend to describe a product, task, or resource, depicted in Fig. 3.3.

As basic attributes, the property has an ID, name, and, optionally, a unit. These attributes are inherited by the types:

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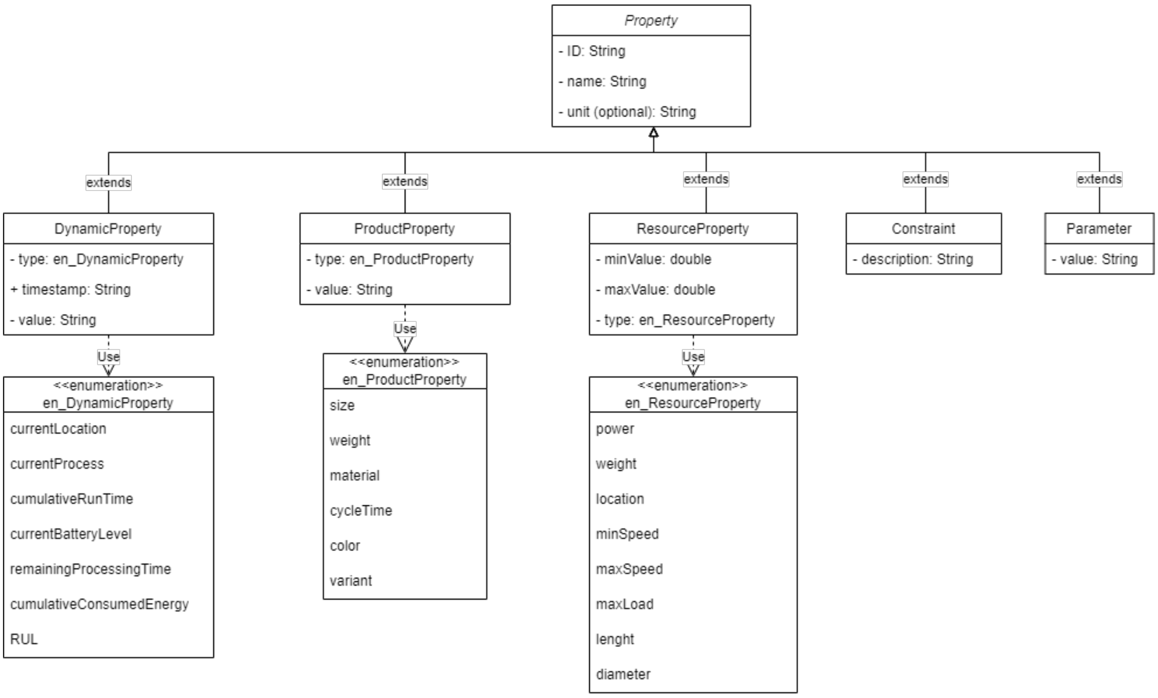

Figure 3.3: Types of properties used in the model

- *DynamicProperty.* Models the properties that can change during the execution of the process. It has a timestamp and value associated with it. A list of predefined properties is available at the 'en_DynamicProperty' enumeration.
- *ProductProperty.* Used for static product properties that are relevant for manufacturing, for instance, size, weight, and material, among others, which are predefined in the 'en_ProductProperty'
- *ResourceProperty.* Describes the resource specifications or functional characteristics as a range with minimum and maximum value. A list of predefined properties is available at the 'en_ResourceProperty' enumeration.
- *Constraint.* This type of property is used for describing a capability's constraint. Due to its diverse nature, it was only modeled as a text description.
- *Parameter.* Specifies the values required to set on a resource for the execution of a task. These values are specified by the 'Template' to configure the resource.

It is worth mentioning that the proposed models do not intend to replace existing standardized representation approaches. On the contrary, the models require those specialized representations to extract the relevant information and apply it within the present framework.

3.3 Multi-agent based negotiation and control logic

Several elements/agents are required to develop the control logic proposed in this framework to achieve the desired level of autonomy and distributed design. Below is a list of the elements presented

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and their description:

3.3.1 Agents description

- Product Agent: Logical abstraction of the physical product. It is responsible for managing the manufacturing details. It has also knowledge of the required manufacturing operations.
- Machine Monitoring Agent: Logical abstraction of the health status of each of the machines. It allows the calculation of variables such as Remaining Useful Life.
- Machine Configuration Agent: Logical abstraction of the specific parameters of the configuration of each of the machines. It interacts with a specific machine providing specific parameters of machine configuration as per the requirements of the product.
- Transport Agent: Logical abstraction of the transport elements of the shop floor. It is mainly responsible for the transportation of the raw material to each specific machine as per the requirements of the product.
- Collection transport group: Element that acts as a directory and stores relevant information of transport agents available.
- Collection machine group: Element that acts as directory and stores relevant information about the machine agents.

Fig. 3.4 presents a sketch of the multi-agent based framework of this approach.

3.3.2 Logical description

The logic of the process starts when a new intelligent product is launched. Each product has at least one task. The tasks are sequentially performed. When a task is launched, it is sent to the collection machine group that will find based on the available data, proper candidate machine agents to perform a task (by a capability matching process). The optimal machine can be selected considering availability, functional machine parameters, and their RUL. As mentioned, each machine agent has a link with a monitoring agent that when launched will return the calculated RUL. After the machine with optimal functional parameters has been selected, the configuration agent will be launched. This will provide specific configuration parameters for the machine. It is based on the specific requirements of the product. As soon as the machine has been configured, an available transport resource will be selected to take the product from its current place to the next one. Once in the workspace of the specific machine, the task will be performed. As soon it is finished the sequential process will be repeated with the next task, until the complete set of tasks have been performed. Fig. 3.5 presents a sketch of logical sequence describe in this paper.

3.4 Machine monitoring

Sensory data like temperature, pressure, machine speed etc. and run time information from machine agents is sent to a data storage. This data transmission could be wired or wireless using IoT devices and the data could be stored at a remote location/cloud severs. The machine monitoring agent utilizes the sensory data stored for data processing to extract valuable insights and information using various techniques such as data mining, machine learning, and statistical analysis for transforming raw data into meaningful information that can be used for decision-making.

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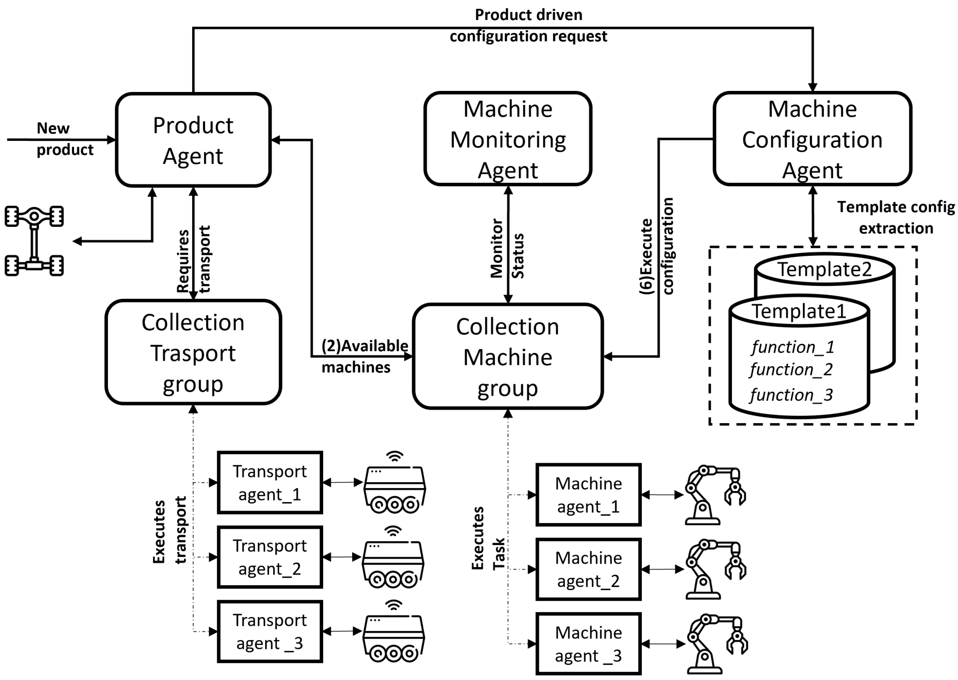

Figure 3.4: Agent-based Framework

Sensor data : Sensor data plays a crucial role in monitoring the operational and environmental conditions of machines or systems. Vibration, temperature, pressure, current, and acoustic sensors are some of the types of data that can be used to monitor equipment condition. Other data, such as historical maintenance records and environmental data, can also be used to develop predictive models for estimating the equipment's future performance. By integrating this data, machine learning techniques can be used to provide valuable insights into the condition and performance of machines and systems, enabling proactive maintenance and minimizing downtime.

Data pre-processing : Data pre-processing prepares data for prediction, as it involves identifying and correcting errors, inconsistencies, or missing data in the collected data set. The goal of data pre-processing is to ensure that the data used for prediction is accurate, complete, and consistent, which is critical for developing a reliable predictive model. This process involves several steps, such as detecting and correcting errors, handling missing data appropriately, removing duplicates, standardizing the data, and validating the pre-processed data set to ensure accuracy and suitability for prediction. By performing data pre-processing, the data set is improved in terms of quality, which enhances the accuracy and reliability of the predictions.

Feature engineering : Feature engineering is used in developing accurate and reliable predictive models for machines or systems monitoring. It involves selecting and transforming raw sensor data into meaningful features that can be used to train a model, such as statistical, frequency, time-domain, wavelet-based, and domain-specific features. The goal is to extract relevant information from sensor data that can predict the condition or performance of the equipment. By scaling or

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normalizing the features and removing any highly correlated or redundant features, the model is based on relevant and meaningful information extracted from the sensor data, which improves the accuracy and reliability of the predictions.

Data Analysis : In Data analysis, processing and interpreting data collected from sensors and other sources to estimate or predict the machine monitoring parameters. Data analysis techniques used in machine monitoring include time-series analysis, statistical analysis, machine learning, feature selection, and model validation. Effective data analysis is essential for developing a predictive model based on high-quality data that can handle various operating conditions and failure modes, ensuring the accuracy and reliability of the predictions. By using data analysis, machine monitoring can be made more efficient and cost-effective, ultimately increasing the uptime and productivity of the machine or system.

Data Prediction: After we perform valid and reliable data analysis, we can identify trends and patterns in the data, forecast future outcomes, optimize processes and systems, and assess potential risks. To achieve this, we need to use appropriate analytical methods that align with our goals and the type of data we are analyzing. By doing so, we can gain valuable insights that will help us make informed decisions and improve our business or organization.

In the context of machine monitoring, data analysis techniques can be used to make predictions such as machine failure, maintenance scheduling, quality control, energy consumption forecasting and production optimization. By analyzing machine data from sensors and historical maintenance records, maintenance teams can take proactive measures to prevent downtime and reduce repair costs. Additionally, analyzing machine behavior patterns can help optimize production processes, increase throughput, and ensure product quality. Overall, these predictions can help improve machine performance, reduce downtime, and optimize production processes.

Knowledge Base: Using a knowledge base for machine monitoring with historical databases, data processing libraries, machine learning libraries, and cloud computing. Historical databases provide us with a record of past events and activities, which we can use to make informed decisions about machine maintenance, production optimization, and quality control. Data processing libraries and machine learning libraries allow us to efficiently analyze large amounts of machine data, enabling us to make accurate predictions about machine behavior, failure, and maintenance needs. With cloud computing, we can store and access our knowledge base from anywhere, enabling us to collaborate and make quick decisions. Overall, our knowledge base built on historical databases, data processing libraries, machine learning libraries, and cloud computing will help us to improve machine performance, reduce downtime, and optimize production processes.

3.5 Optimal Machine Selection

The selection of the optimal machine for a specific task is a critical decision in manufacturing and production environments, as it directly influences overall productivity, efficiency, and product quality. This decision is contingent upon various criteria, such as cost, reliability, performance, energy consumption, reachability, payload, availability, utilization rate, and changeover time. In this paper, we propose a comprehensive optimal machine selection process that integrates machine monitoring data and multiple criteria, assigning fixed or random weights to each criterion. This methodology offers a systematic approach for decision-makers to choose the most appropriate machine according to their specific needs and priorities, ultimately enhancing productivity, efficiency, and product quality.

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3.5.1 Criteria for Machine Selection

The following criteria are considered for machine selection:

1. Cost (C): The initial investment, operation, and maintenance costs of the machine.
2. Reliability (R): The probability of the machine performing without failure during its operational life.
3. Performance (P): The efficiency, speed, and accuracy of the machine.
4. Energy Consumption (E): The amount of energy consumed by the machine during operation.
5. Reachability (RE): The workspace and accessibility of the machine.
6. Payload (PL): The maximum load the machine can handle.
7. Availability (A): The percentage of time the machine is available for use.
8. Utilization Rate (UR): The ratio of the machine's actual working time to its available time.
9. Changeover Time (CT): The time required for the machine to switch between tasks or products.

3.5.2 Assigning Weights to Criteria

Weights can be assigned to criteria based on the decision-maker's preferences. The sum of all weights should be equal to 1. There are two approaches for assigning weights:

1. Fixed Weights: The decision-maker assigns fixed weights to each criterion based on their priorities. For example, if cost is the most important factor, it might be assigned a higher weight than the other criteria.
2. Random Weights: Weights can be randomly generated for each criterion within a specified range, allowing for a stochastic analysis of the machine selection process. This can be useful in scenarios where the decision-maker is uncertain about the relative importance of each criterion.

3.5.3 Incorporating Machine Monitoring Data

Machine monitoring data, as elucidated in the previous section, plays a pivotal role in the optimal machine selection process. By leveraging machine monitoring data, decision-makers can make more informed choices that consider the real-time condition and performance of machines.

Integrating Machine Monitoring Data

To integrate machine monitoring data into the selection process, we can include additional criteria or update the existing criteria values based on the monitoring data. For instance, we can consider the following supplementary criteria:

1. Historical Machine Performance (H): The historical performance of the machine based on monitoring data, which can provide insights into the machine's long-term efficiency and productivity.

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2. Predicted Machine Failure (F): The predicted probability of machine failure based on machine monitoring data, which can be used to estimate the machine's reliability and maintenance requirements.

These new criteria can be integrated into the weighted sum model by extending the sum in Equation (3.1) to encompass the additional criteria.

$$S_i = \sum_{j=1}^{k} w_j C_{ij} \tag{3.1}$$

where k represents the total number of criteria considered, including the initial criteria and the additional criteria based on machine monitoring data, i represents the index of a specific machine under consideration. For example, if there are multiple machines being evaluated for optimal selection, i would vary from 1 to the total number of machines being compared. The score, S_i, represents the weighted sum of the criteria values for the i^{th} machine, which is used to rank and compare the machines based on their suitability according to the defined criteria and their respective weights.

By incorporating machine monitoring data in the form of additional criteria or by updating existing criteria values, the selection process becomes more robust and reflects the real-time conditions and historical performance of the machines under consideration. This integration enables decision-makers to make better-informed choices, leading to improved machine performance, reduced downtime, and optimized production processes.

Updating Criteria Values

Machine monitoring data can also be used to update the existing criteria values based on real-time information. For example, the reliability criterion (R) can be updated with the latest failure prediction data, and the maintenance requirements criterion (M) can be updated based on the current maintenance scheduling and historical maintenance records. By continuously updating the criteria values with machine monitoring data, the optimal machine selection process remains dynamic and adapts to the changing conditions of the machines.

3.5.4 Comprehensive Optimal Machine Selection Process

The optimal machine selection process, incorporating machine monitoring data and expanded criteria, can be summarized as follows:

1. Define the criteria for machine selection, including cost, reliability, performance, energy consumption, reachability, payload, availability, utilization rate, and changeover time.

2. Determine the additional criteria based on machine monitoring data, such as historical machine performance and predicted machine failure.

3. Integrate the machine monitoring data into the selection process by updating the existing criteria values or including the additional criteria.

4. Assign fixed or random weights to each criterion based on the decision-makers preferences or by using a stochastic approach.

5. Calculate the score for each machine using the extended weighted sum model (Equation (3.1)), taking into account the updated criteria values and weights.

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6. Select the machine with the highest score as the optimal choice.

By implementing this comprehensive optimal machine selection process, decision-makers can leverage machine monitoring data and expanded criteria to make more informed choices, leading to improved machine performance, reduced downtime, and optimized production processes. This structured approach ensures that the selection process is logical, adaptable, and in line with academic standards, providing a solid foundation for future research and practical applications in the field of machine monitoring and selection.

3.6 Machine configuration specification

Figure 4.2 illustrate the machine configuration component in the proposed architecture. The detail on the machine configuration change specification can be seen in the figure 3.8. The manufacturing asset is represented by the asset administration shell (AAS) containing functionality submodels. The machine configuration change specification component checks/iterates over these submodels for configuration updates and decision-making.

The machine configuration specification component checks the representative functionality hosted by AAS in their functionality submodels. The configuration update is carried out through the following steps:

- The agent interacts with the functionality submodel information by iteration over each submodel.
- Each submodel is extracted and loaded by the agent in the memory. Preliminary comparison and analysis is carried out based on trained models. These trained models complement the objective and constraint requirements on the manufacturing asset. To continuously improve the runtime check performance, the result from the comparison and analysis is sent back to the centralised data store through a connector to ERP/Cloud.
- If after the comparison and analysis, the conditions are satisfied then the next submodel can be iterated, extracted and loaded in memory to repeat the process. If the condition is not satisfied, then the respective deviation is noted as an alarm in the Alarm Store. The next submodel can then be iterated to repeat the process.
- The results are aggregated to represent the total machine configuration specification for all functionalities in the manufacturing asset. This aggregation takes into account the results obtained from results and analysis, the alarm log from the Alarm Store and the manufacturing asset objectives/constraints.
- If the results are considered to be satisfactory, then the runtime monitoring check component returns an "OK" to the agent, else returns a "Not OK". These signals can easily be switched/integrated to the PLC I/O signals with the agent interacting with them.

In the developed approach for machine configuration, as mentioned in the steps above, the need for configuration is identified by first iterating over functionality submodels. The changes, through the procedure mentioned, are identified. This starts the machine reconfiguration process planning. The machine configuration specification component executes the configuration change. Testing/validation and continuous monitoring are carried out by iterating over submodels.

First, we need to generalise the machine configuration specification component. We propose that the machine configuration specification is a step-wise procedure. Each step encapsulates some aspects of the machine configuration setup. These steps are;

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- **Detecting the need** This step involves monitoring the production system to detect changes in the production environment that may require a reconfiguration of one or more machines. This could include changes in production demand, machine failures, or changes in the production schedule.
- **Identification of machine reconfiguration** Once the need for reconfiguration is detected, the next step is to identify the specific machines that need to be reconfigured. This could involve analyzing data from the production system to determine which machines are affected by the change in the production environment and need to be reconfigured.
- **Plan the reconfiguration** This step involves planning the details of the reconfiguration, including the specific changes to be made to the machines, the resources needed to perform the reconfiguration, and the sequence of steps to be taken. This step may also involve simulating the proposed reconfiguration to ensure that it will be successful and to identify any potential issues that need to be addressed.
- **Execute the reconfiguration** Once the reconfiguration has been planned, the next step is to execute the changes. This may involve physically reconfiguring the machines, updating software configurations, or adjusting control parameters.
- **Testing and Validation** After the reconfiguration has been executed, it's important to test and validate that the machines are configured correctly and that the system is operating as expected. This may involve running tests on the machines and monitoring the system to ensure that it is functioning correctly.
- **Monitoring and Maintenance** Finally, it's important to monitor the system after the reconfiguration and make any necessary adjustments to maintain the desired configuration.

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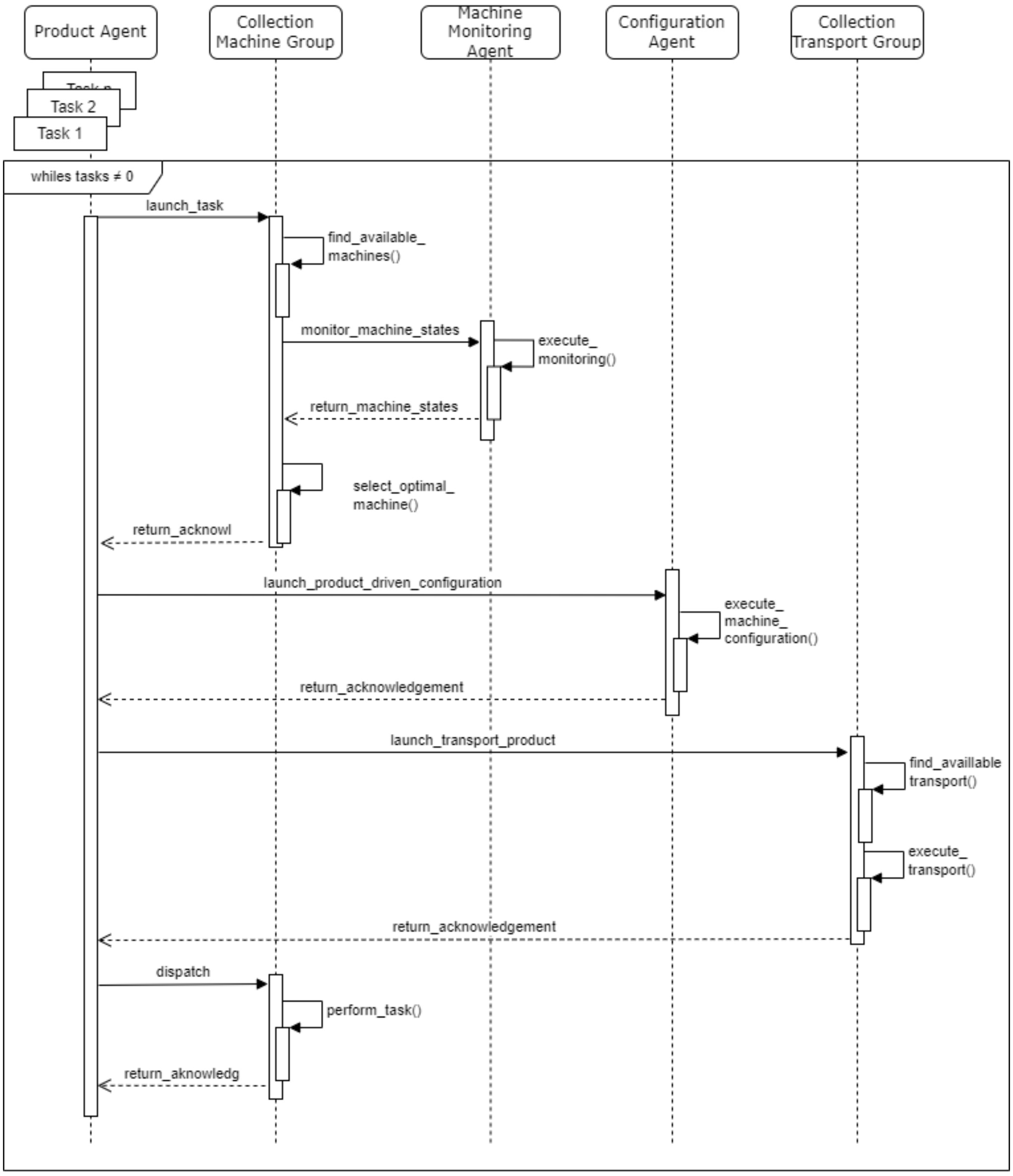

Figure 3.5: Sequence diagram

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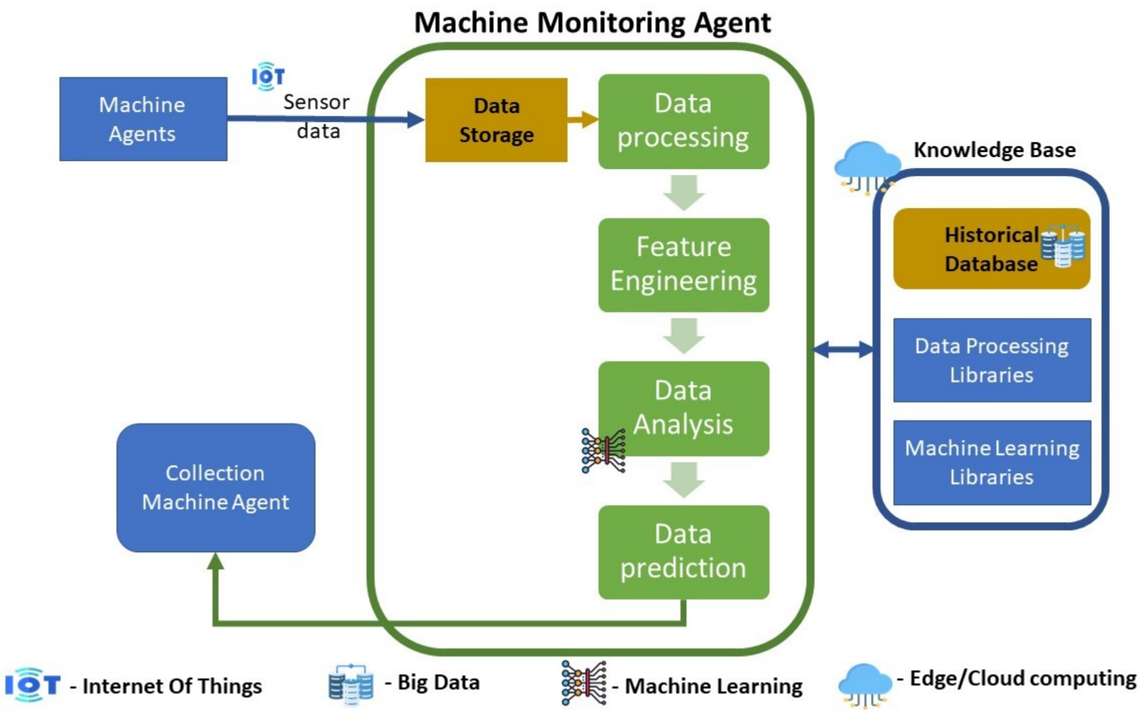

Figure 3.6: Machine monitoring Agent

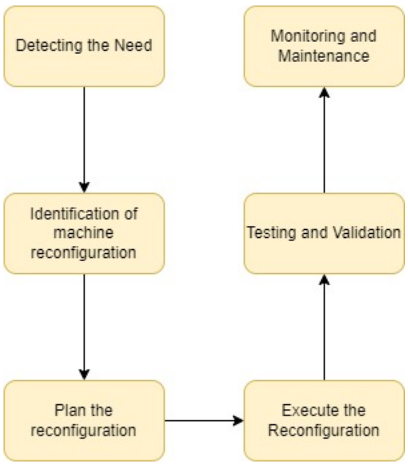

Figure 3.7: Approach for self-configuration within the framework

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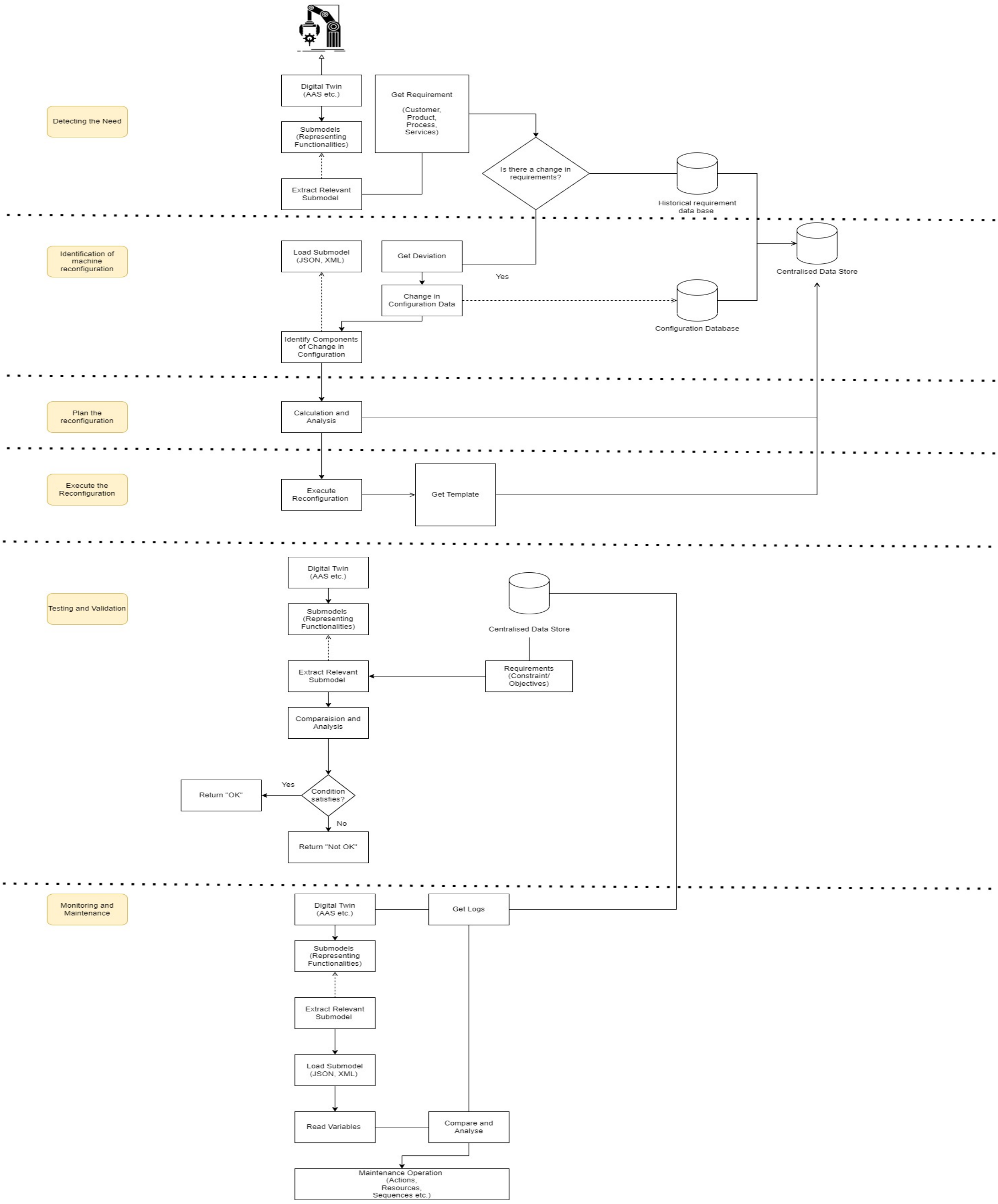

Figure 3.8: Detailed machine configuration change specification

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Chapter 4

Conceptual Use Case

The current chapter presents the applicability of the presented framework with a specific proof of concept. At his stage of the work the implementation remain conceptual.

4.1 Conceptual Scenario

4.1.1 Product: Manual Expanding Mandrel

A manual expanding mandrel is a tool used in metalworking and woodworking to hold and expand a workpiece. It typically consists of a cylindrical body with several slits cut into it, and a tapered wedge or screw that can be driven into the slits, causing the mandrel to expand and grip the inside of the workpiece. The manual expanding mandrel is then held in a lathe or other machine to facilitate turning or drilling operations on the workpiece [37]. Manual expanding mandrels are often used in situations where a workpiece cannot be held securely by conventional methods, such as when working with irregularly shaped or delicate materials. They can be adjusted by hand to fit a wide range of workpiece sizes, making them a versatile and useful tool in many different applications. The manual expanding mandrel is used in the context of the presented framework as it is a representative example of a single-piece product. Its design allows the definition of specific sequential tasks to be delegated by available resources in the shop-floor.

Figure 4.1: Manual Expanding Model as a proof of concept product, from [37]

4.1.2 Scenario: Flexible manufacturing shop-floor

As part of the conceptual use case, we present a flexible manufacturing shop-floor. The scenario has been developed considering the various stages of manufacturing of the manual expanding mandrel (will be detailed in next section). Key aspects of the scenario are the flexibility in terms of routing (flexible transportation provided by AGVs), different routes for movement, and redundancy of resources.

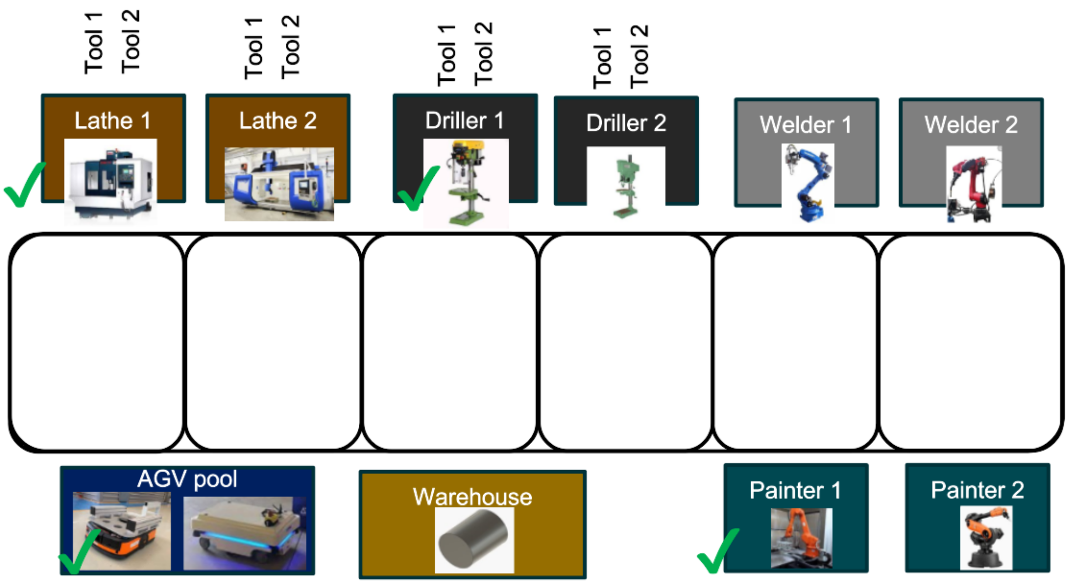

Figure 4.2: Approach for self-configuration within the framework

4.2 Product modeling

As mentioned above, the manual expanding mandrel was selected as a studied product, although a plain version was used throughout the study for simplification purposes. The manufacturing process of the studied product was summarized in five tasks, as shown in Fig. 4.6:

- Task 1 (TK1): starting from a cylindrical bar, a turning operation is required. This operation is executed until obtaining the profile delimited by points P1 to P7-E.
- Task 2 (TK2): with the same setup, a second turning operation is required to shape the profile delimited by points P8 to P12.
- Task 3 (TK3): once the main shape is achieved, a face grooving operation follows, to obtain the groove by sweeping the profile defined by points P13 to P16 (detail A).
- Task 4 (TK4): a drilling operation is needed to create six throughout holes, according to the product's drawings (in Appendix).

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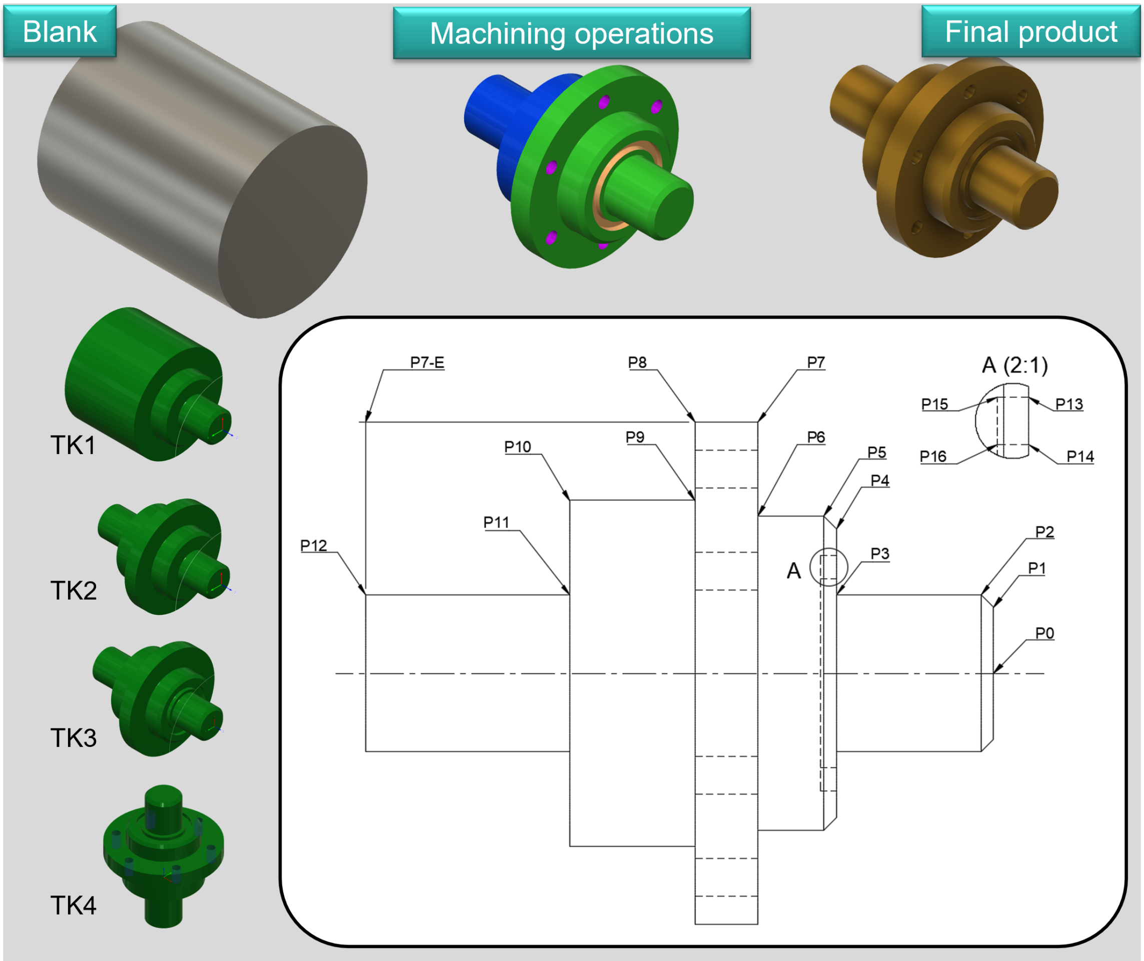

Figure 4.3: Product, associated tasks, and profile references for machining operations

- Task 5 (TK5): a final painting operation is required to deliver the product in its final state.

The described tasks are to be executed sequentially, with the minimum number of setups, with the resources available on the shop floor.

The model proposed in this work is fed with the product properties, the variables that are going to be registered in real-time, and the tasks needed for its manufacturing. Each task specifies the capabilities required and their constraints, besides the variables used for monitoring. The resulting model is depicted in Fig. 4.4.

It should be noticed that the information required to fill out the model can be extracted from different sources, such as the geometrical model of the product, or the process plan. The main goal is to structure the existing information in a clear way so it facilitates its usage by the different algorithms and processes towards a self-configuration approach.

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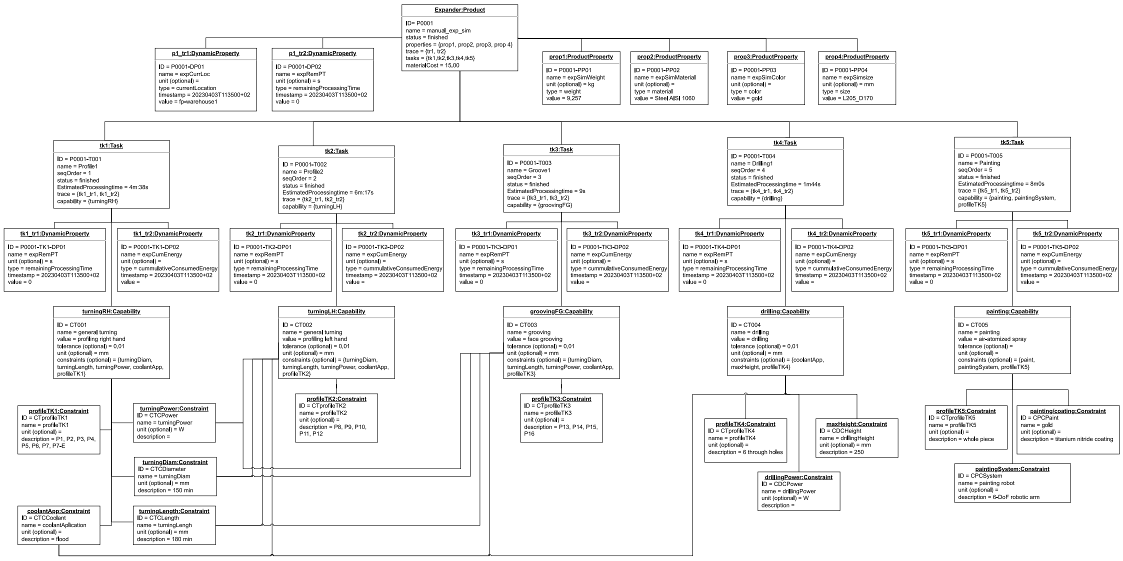

Figure 4.4: Studied product according to the proposed model

4.3 Resource modeling

In the same way as the studied product, the resources available on the shop floor were outlined following the proposed model. Fig. 4.5 shows three examples of the modeled resources, with their respective skills, specifications, and the data they provide for process monitoring. It is worth mentioning that the model was able to accommodate the different types of resources independent of their complexity.

4.4 Infrastructure negotiation specification

To conceptually showcase the applicability of our proposed framework and proposed product, we will consider the first stage of its manufacturing process, as this is iterative for the other tasks.

The five agents proposed in the previous chapter of the deliverable are instantiated to showcase this negotiation.

4.5 Monitoring component specification

Predicting the Remaining Useful Life (RUL) of a machine can be a useful tool for making informed decisions about whether to repair or replace a machine, and for choosing optimal machines for an organization. The sensor data required to predict the Remaining Useful Life (RUL) of a turning machine are,

1. Vibration - dynamic behavior like indicate wear, misalignment, or damage to components
2. Temperature - thermal behavior indicating overheating or component degradation
3. Power consumption - power requirements indicating excessive wear or damage to components

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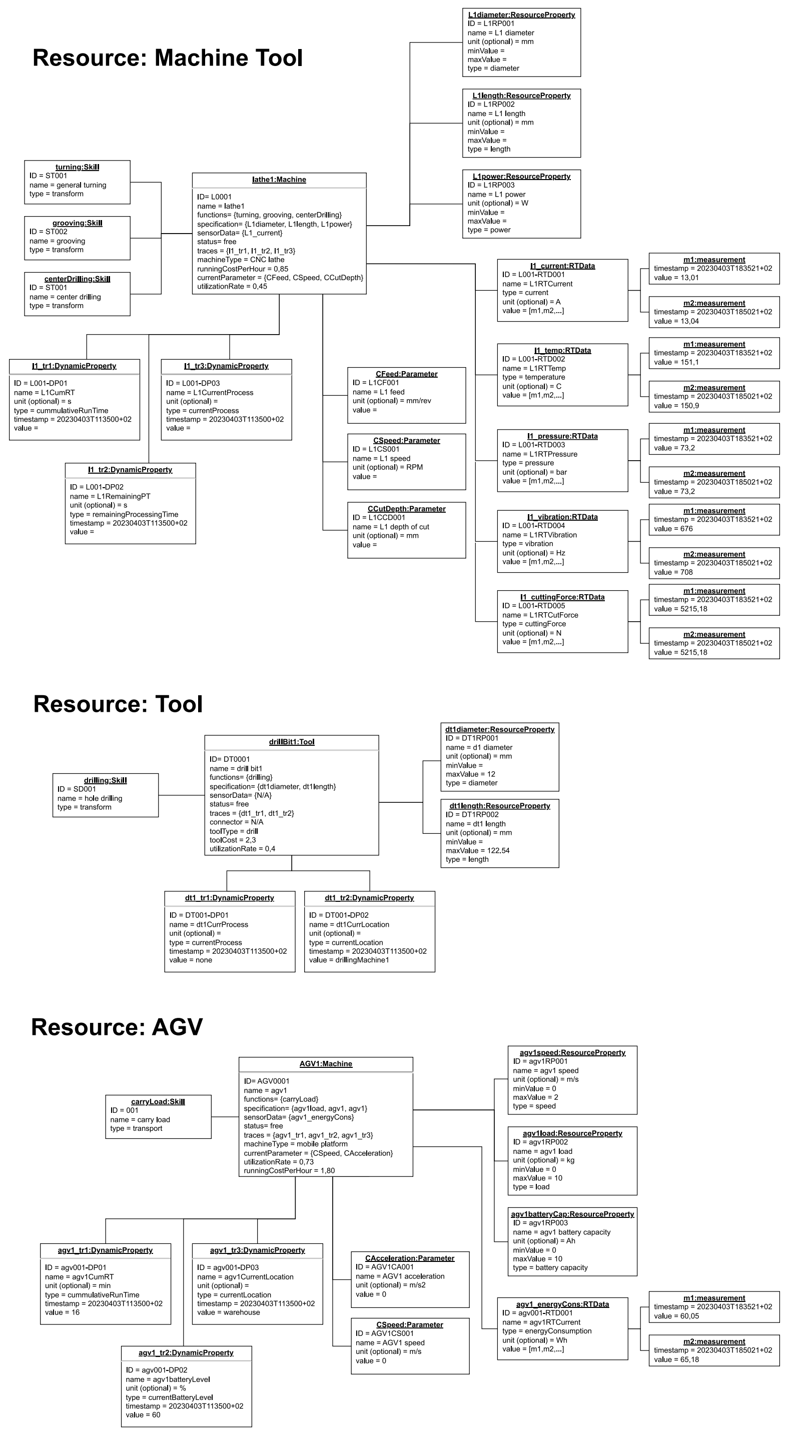

Figure 4.5: Lathe, cutting tool, and AGV represented according to the proposed model

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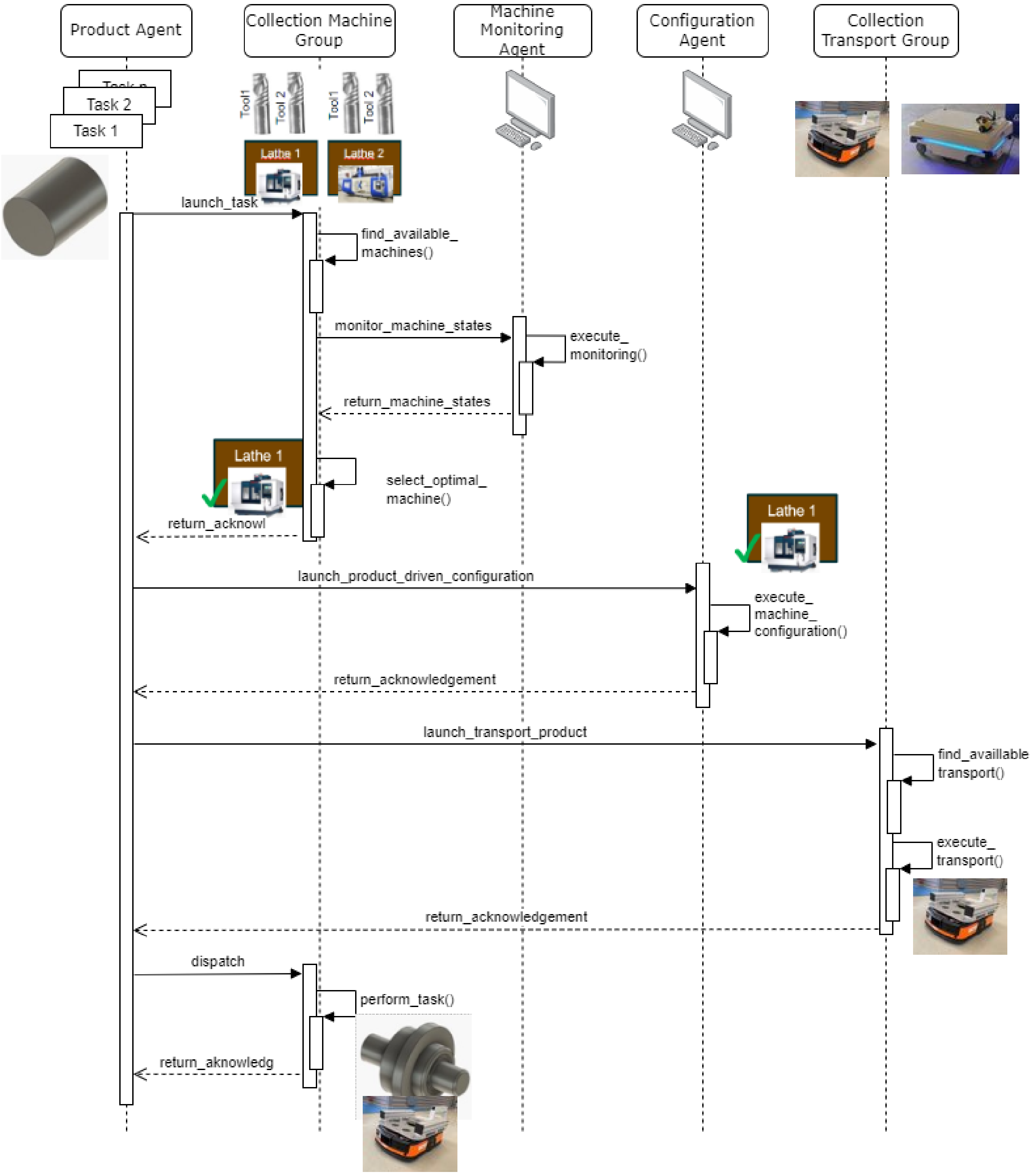

Figure 4.6: Process negotiation for proof of concept of the product

4. Acoustic - sound behavior indicating bearing wear or other mechanical problems

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5. Pressure - fluid behavior, which can indicate clogging or wear in pipes or valves

To predict the Remaining Useful Life (RUL) of a CNC lathe, there are multiple techniques available, each with its own strengths and weaknesses. The most suitable technique depends on the specific needs and constraints of the application. For instance, statistical approaches such as the Proportional Hazards Model are useful when the data is well-behaved, while machine learning approaches are advantageous when there is a large amount of data or complex relationships between the sensor data and RUL. Model-based approaches are effective when there is a clear understanding of system dynamics and parameters. Hybrid approaches can combine multiple techniques to create more accurate predictions. By using a combination of techniques, maintenance teams can create more accurate and robust predictions, leading to better maintenance planning and reduced downtime and maintenance costs. here, a Neural network based approach is used for the RUL prediction due to the complex relationship between sensor data and RUL. Below, we present a pseudo-code for using a neural network to predict the Remaining Useful Life (RUL) of a CNC lathe:

Algorithm 1 RUL Prediction of CNC Lathe Machine using Neural Network

```
procedure RUL Prediction
    training_data ← collect_and_preprocess_data(vibration, temp., power, acoustic, pressure)
    network_model ← train_neural_network(training_data)
    validation_data ← collect_and_preprocess_data(sensor_data)
    accuracy ← validate_network(network_model, validation_data)
    new_data ← collect_and_preprocess_data(sensor_data)
    predicted_RUL ← predict_RUL(network_model, new_data)
    if predicted_RUL < threshold then
        plan_maintenance()
    else
        continue_operation()
    end if
    if RUL_information_requested then
        send_data(RUL_information)
```

The pseudo-code outlines the basic steps involved in predicting the Remaining Useful Life (RUL) of a CNC lathe using a neural network with sensor data. The first step involves collecting and preprocessing historical sensor data to create a training dataset. The neural network is then trained on the training dataset, and in the third step, it is tested and validated using a separate validation dataset to evaluate its performance and fine-tune the model if necessary. The fourth step involves predicting the RUL for new sensor data using the trained neural network.

4.6 Optimal machine selection specification

The optimal machine selection is crucial for the efficient and effective manufacturing of a product. The proposed framework takes into account the specification of the product and the capabilities of the available resources on the shop floor to determine the optimal machine selection.

To select the optimal machine for a given task, the proposed framework follows a two-step process. In the first step, the framework identifies the candidate machines that have the necessary capabilities to perform the task. In the second step, the framework selects the optimal machine from the candidate machines based on criteria such as availability, utilization, and efficiency.

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The candidate machines are identified by comparing the capabilities required for the task with the capabilities of the available machines. The capabilities required for a task are defined in the product model, while the capabilities of the available machines are defined in the resource model. The capabilities comparison can be performed using a simple matching algorithm that compares the required and available capabilities.

Once the candidate machines have been identified, the framework selects the optimal machine based on criteria such as availability, utilization, and efficiency. The availability criterion takes into account the current status of the candidate machines, such as whether they are currently in use or undergoing maintenance. The utilization criterion takes into account the historical utilization of the candidate machines, such as how frequently they have been used in the past. The efficiency criterion takes into account the performance of the candidate machines, such as their energy consumption and production rate.

The optimal machine selection can be performed using a decision-making algorithm that assigns weights to each of the criteria and calculates a score for each candidate machine. The machine with the highest score is then selected as the optimal machine for the task.

In conclusion, the proposed framework takes into account the product specification and the capabilities of the available resources on the shop floor to determine the optimal machine selection for a given task. The two-step process involves identifying the candidate machines that have the necessary capabilities and selecting the optimal machine based on criteria such as availability, utilization, and efficiency. By using this approach, the manufacturing process can be optimized, leading to increased efficiency, reduced downtime, and lower costs.

4.7 Configuration specification

The machine configuration specification defines the requirements for configuring a machine to produce a specific mechanical part. The specification includes the necessary parameters and settings for the machine, such as the tooling, cutting speed, and feed rate.

To create a machine configuration specification, the requirements for the mechanical part are analyzed to determine the optimal configuration for the machine. This analysis takes into account factors such as the material of the part, the required precision, and the production volume. Once the optimal configuration is determined, it can be specified in a machine configuration specification document.

The machine configuration specification can be integrated with an Asset Administration Shell (AAS) to manage and monitor the machine's configuration. The AAS can contain multiple submodels, each representing a different aspect of the machine's functionality. For example, one submodel could represent the machine's cutting tool, while another submodel could represent the machine's material feed system.

When a change in the mechanical part requirements occurs, components in the system can detect the need for a configuration change. The type of reconfiguration needed can then be identified, and a plan for the reconfiguration can be created. Finally, the machine configuration can be updated, allowing the machine to produce the new mechanical part.

Overall, the machine configuration specification and the integrated AAS provide a powerful framework for managing and optimizing the configuration of a machine to meet the changing demands of modern manufacturing.

In addition to the previous components, the expanded class diagram includes an optimal machine selection component. This component is responsible for selecting the most suitable machine for the specific production requirements based on factors such as machine availability, machine capabilities,

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and production schedule.

The optimal machine selection component receives input from the production planning component, which provides information about the part to be produced, the required production volume, and the production schedule. The optimal machine selection component then evaluates the available machines and selects the most appropriate one based on the input parameters.

This component also takes into account other factors such as the machine's efficiency, maintenance status, and previous production history. By selecting the optimal machine for production, this component can help to minimize downtime, reduce production costs, and optimize the overall production process.

Overall, the expanded class diagram with the optimal machine selection component provides a comprehensive solution for machine configuration specification that takes into account the specific requirements of each production order and ensures efficient and effective use of available machines.

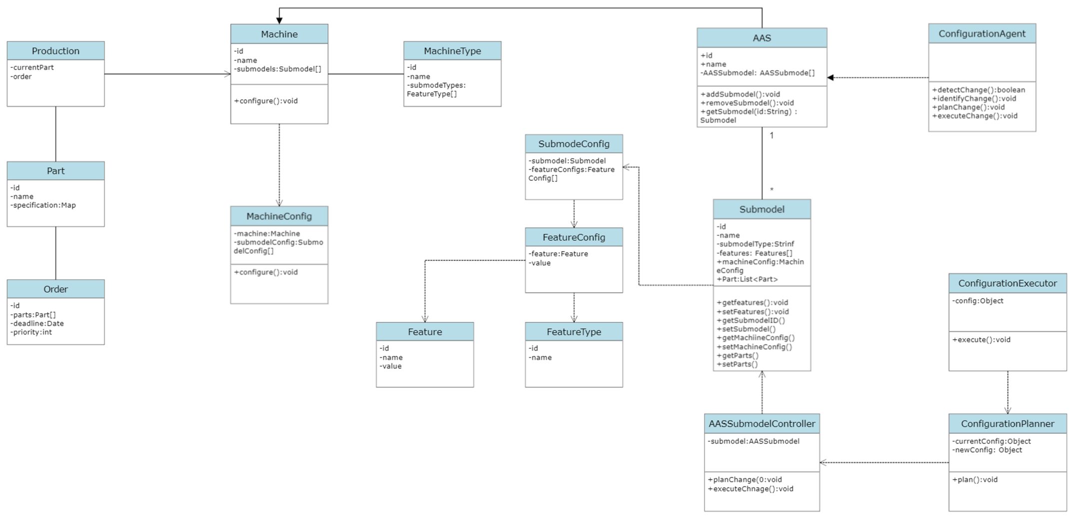

Figure 4.7: The UML Class diagram of Machine configuration specification for the optimum configuration selection based on proposed approach. The machine selection drives the configuration change process where the machine is configured to meet requirements of the part.

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Chapter 5

Discussion and Conclusions

This study set out to present a comprehensive framework for self-configuring production. The framework comprised a data model according to the product-process-resource paradigm, a multi-agent system scenario with machine monitoring and optimal resource allocation, and finally, a machine configuration strategy.

Higher levels of product customization require decentralized control approaches. Such infrastructure has been implemented using multi-agent negotiation in this work. Particularly, we focus on product-driven manufacturing of batch-size one. The multi-agent infrastructure proposed integrates a product/resource negotiation to control manufacturing assets and components for monitoring, configuration, and optimization of the whole system. Such infrastructure aims to increase the flexibility and adaptability of shop-floor operations.

The framework has been conceptually showcased using the manual expanding mandrel as an example and a shop floor with flexible transportation. Overall, this shows the advantages of the solution in a real-life scenario and the flexibility it can provide.

Well-defined data models facilitate the exchange of information between the different actors in a manufacturing scenario. Considering the intelligent product paradigm, the product itself is the main information carrier, Therefore, all operations required for a product realization need to be determined by the product and communicated to the resources available on the shop floor. These tasks need to be allocated based on the capabilities that the manufacturing tasks demand and the skills the resources could provide. An explicit and clear representation of capabilities and skills is essential for achieving an accurate matching between task and resource. The matching process can be streamlined by the use of intermediary entities such as the template proposed in this work, which can relate the capability and the corresponding skill, as well as the parameters, constraints, and programs specifically established for the task execution. If the OEM provides the resource's skill description with predefined templates applicable to different manufacturing operations, only the parameter calculation will be needed to complete the data, then the matching process will be mostly used for optimization purposes.

The machine configuration specification is a process that involves specifying the configuration requirements for a machine to produce a particular part. It includes selecting the appropriate machine and its sub-models, detecting the need for a configuration change due to part requirements, identifying the type of reconfiguration required, planning the reconfiguration, and executing the machine configuration update. To achieve this, the system makes use of Asset Administration Shell (AAS), which is a standard for representing the physical and virtual assets in a smart factory. The AAS consists of multiple sub-models, each representing different functionalities of the machine. The sub-models are updated based on the machine configuration requirements. The system also includes optimal machine selection, which involves selecting the most suitable machine for the given production requirements. The optimal machine selection process considers factors such as production volume, part complexity, and available machines. To facilitate the machine configuration specification process, the system uses a user interface that allows the operator to input the part requirements and receive recommendations for machine selection and configuration. The system also includes a database that stores information about the available machines and their sub-models. Overall, the machine configuration specification process is a crucial step in the manufacturing process, as it ensures that the right machine is used to produce the required part efficiently and effectively. The integration of AAS and optimal machine selection further enhances the accuracy and efficiency of the process.

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Chapter 6

Appendix

Drawing representing the proposed use case.

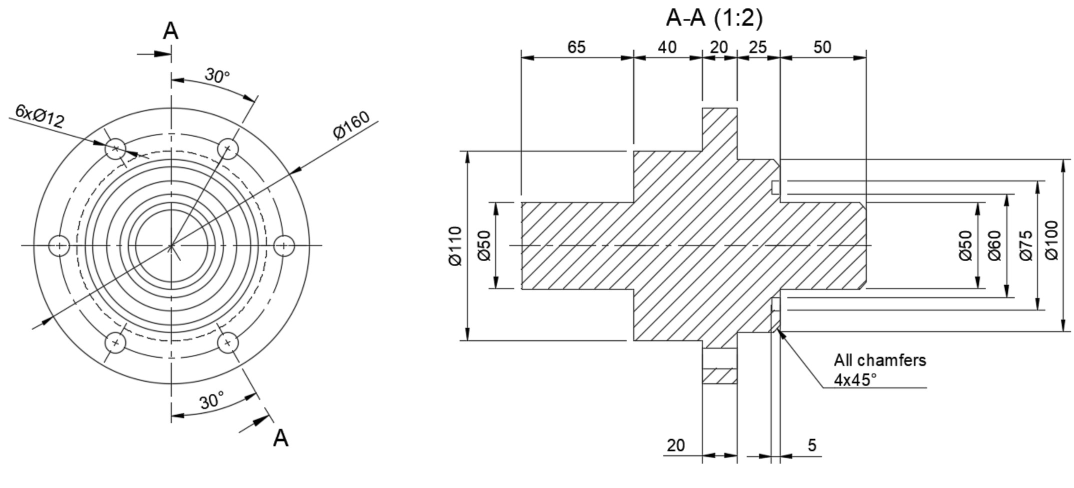

Figure 6.1: Drawing representing the proposed used case

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