The Digital Manufacturing and Design Training Network

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Results of Test Cases

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Contents

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Summary

The manufacturing industry is currently undergoing a significant transformation with the advent of the fourth industrial revolution. This shift necessitates extensive research in areas such as smart maintenance and production automation, particularly in self-configuration systems. To truly understand the implications and benefits of these concepts, it is crucial to showcase real-world test cases and pilot studies, providing insights into how companies can effectively implement these procedures. This report presents two specific approaches aligned with smart maintenance and machine self-configuration systems, which stem from previous deliverables aiming to unify, conceptualize, and present a framework. The first use case demonstrates machine configuration based on a product-driven manufacturing approach, utilizing a Fanuc robotic platform as a test case. The second use case focuses on a tool wear monitoring bench, where the main objective is to predict tool wear using an immune bio-inspired approach. Both use cases offer substantial advantages over traditional solutions in terms of flexibility and adaptability, highlighting their potential for enhancing manufacturing processes.

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Foreword

DiManD aims to develop a high-quality multidisciplinary, multi-professional, and cross-sectorial research and training framework for Europe. The purpose is to improve Europe's industrial competitiveness by designing and implementing an integrated programme in the area of intelligent informatics-driven manufacturing, which will form the benchmark for training future Industry 4.0 practitioners. This will be done in compliance with the industrial requirements such revolutionary production systems will pose, and specifically, this deliverable will represent one further step forward, by attempting to design and validate two frameworks and by providing pilot use cases for its validation. In particular, this deliverable will showcase a self-monitoring and self-diagnosis approach (based on the artificial immune system) and a self-configuration-based manufacturing system. The main design patterns will be summarized as well as the application of them in an experimental setup.

1 Introduction

1.1 Self-configuration in manufacturing

Industry 4.0 has reshaped manufacturing with IoT, AI, and big data. Companies now need adaptable production systems that autonomously optimize efficiency and quality. To meet this need, self-configuring systems that adjust in real-time have become crucial. Integrating multi-agent systems and new emerging technologies seems a promising path to creating this level of adaptability.

1.1.1 Manufacturing self-configuration - Definition

Under the scope of this work, we consider self-configuration as: *It is the ability of a system to change its configuration (i.e., the connection between different system modules, parameters, and calibration) in order to improve or restore system functionality in response to actions* [1].

In manufacturing processes, products with different requirements need different resource configurations. This configuration update is usually carried out manually which is not very effective considering current market dynamism.

This has been partially solved by the introduction of flexible manufacturing systems or Supervisory Control and Data Acquisition (SCADA) systems. However, those usually operate under a predefined working envelope defined by the part family, reducing its capacity of adaptation. Thus, the need of having the ability of robotic platforms to self-configure considering new production specifications.

1.1.2 Refined stated of the art and Gap analysis

Several studies have suggested self-configuring manufacturing. In one framework detailed in [1], they propose using agent technologies and a cloud pipeline to find the best setup parameters. Another idea in [2] suggests self-configuring a plug-and-produce system using a service-oriented workflow manager. Other research focuses on process configuration using agent technologies, ontological models (like in [3, 4, 5, 6, 7]), or web services (as discussed in [8]).

Most of these methods assume that resources either come pre-equipped with a set of skills or rely on a central platform to coordinate services or provide new capabilities. However, the rapidly changing market and unexpected events, like the Covid-19 pandemic prompting automakers to shift to manufacturing medical equipment, highlight the limitations of such predefined approaches. Relying heavily on a centralized unit's knowledge can pose risks—if it fails, the entire manufacturing process suffers. Thus, emphasizing the importance of resource self-configuration independent of a centralized system, capable of adapting at runtime without additional updates, driven solely by product requirements (referred to as intelligent produce-driven manufacturing [9]).

1.1.3 Contribution of the current framework

Our goal is to address this challenge by introducing a framework for self-configuring robotic platforms. This framework assumes a self-organizing process where raw materials are transported to specific robotic platforms, possibly using Automated Guided Vehicles (AGVs). This concept responds to the need for self-management in highly flexible shop floors, such as the matrix production concept developed by KUKA, where logistics and production components operate independently [10]. In this matrix production, a fleet of AGVs handles end effectors and raw materials for production cells, enabling versatile production that can adapt quickly to new requirements [10].

Our focus is on creating a framework that allows robotic platforms to configure themselves within an intelligent product-driven manufacturing setup, with a strong emphasis on software integration. The product itself holds crucial information about operations, parameters, and configurations, transmitting these details to the robotic platforms through a Multi-Agent Architecture. Details about the framework and its components are outlined in the next section of the report.

1.2 Self-diagnosis and self-monitoring in manufacturing

1.2.1 Smart Maintenance

Advancements in computer technology have facilitated the creation of intelligent maintenance frameworks. These systems forecast potential failures beforehand and assist in decision-making for maintenance tasks. These frameworks employ three main methods: mathematical modeling, simulation, and data analysis. They leverage emerging technologies such as:

1. IoT and Cloud: Sensors linked through IoT, alongside Cloud technology for data handling, enable the real-time transmission and processing of shop floor data.

2. Machine Learning: Enhanced mathematical models and ML algorithms enable precise predictions regarding machine conditions and maintenance needs.

3. Big Data: The capacity to gather, transmit, store, process, and visualize large datasets from the shop floor facilitates the effective use of advanced ML and data visualization techniques for accurate maintenance decisions.

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4. Multi-Agent Systems: Utilizing agents capable of independent tasks and collaboration aids in developing resilient and decentralized maintenance systems.

5. Digital Twin: Virtual representations of physical systems assist in creating simulated environments for pre-failure testing and remote access to physical setups.

6. Augmented Reality: AR supports operators in real-time machine condition monitoring and provides adaptive guidance for necessary adjustments.

Limitations of existing frameworks: The emerging technologies have high potential in developing a smart maintenance system in satisfying the new requirements like robustness, adaptability, resilience, anti-fragility and pro-activity [11]. There exists a need for integrating these technologies to fully utilize their combined benefits. Also, all the developed approaches depend on these current technologies and is not based on a future proof framework. There is also a need for a future proof framework which could easily adapt to newly developed technologies and also satisfy new smart maintenance requirements.

1.2.2 Smart Maintenance based on the Immune System - Gap analysis

An immune system-based maintenance framework applies principles from the human immune system to manage manufacturing equipment and processes on the shop floor. It detects and responds to anomalies, defects, and failures.

The human immune system is a vast and intricate network found throughout the body, composed of various cells, proteins, and organs such as the thymus and spleen. It has evolved over billions of years to protect against bacteria, viruses, fungi, and cancerous cells.

Artificial immune systems, inspired by the human immune system, are a focus of engineering research. They involve abstracting, designing, and implementing models using mathematical algorithms and computational techniques. Early applications included fault diagnosis in sensory networks.

The immune system-based maintenance framework incorporates immune mechanisms to develop a predictive and adaptive system. Key mechanisms include the danger model, negative selection, and clonal selection. These mechanisms mimic how the immune system responds to threats by detecting intruders, distinguishing between healthy and infected cells, and producing antibodies to combat invaders.

1. Danger Model: The healthy cells which was damaged due to the intruders/infected cells sends panic signals which is attracted by the Dendritic cells and these cells collects a sample of the intruders (antigen) for selecting the appropriate T-cells.

2. Negative selection: T-cells are designed to identify the difference between the body cells and infected/foreign cells. This knowledge is crucial is preventing the immune system from attacking healthy human cells.

3. Clonal selection: Once a specific B-cell is identified by the T-cell, the B-cell starts producing copy of itself (cloning) and the cloned B-cells produce antibodies which help in attacking the intruders.

Table 1 lists highly cited publications which uses immune system as the base for developing a fault diagnosis and maintenance system. Very few paper tried to develop a framework considering more than one immune mechanism. Laurentys et. al. [12] developed a decision support system considering negative selection and danger model where immune response was triggered by alarms. The same author in a later publication [13] presented a zero sum balance mechanism for identifying harmful activities by considering natural killer cell activation & education. Araujo et. al. [14] showed a framework for a "self" and "non-self" dynamic pattern recognition model inspired by negative and clonal selection. Thumati et. al. [15] developed an online approximator for fault detection in axial piston pump by using negative selection and memory cell intelligence capabilities. In an monitoring application outside of shop-floor, Chen et. al. [16] demonstrated an adaptive immune response pattern recognition algorithm based on negative & clonal selection for detecting structural damage pattern in steel bridge structure.

Limitations of existing frameworks: Proposed frameworks consider the interaction between 2-3 cells (Immune system consist of 21 different cells and 2 protein forces) which doesn't provide the full picture of the human immune system. In fact, immune system protects us by providing two types of immunity - Innate & adaptive. All the proposed mechanisms in the literature focuses on the adaptive immunity. Innate immunity is essential for quick detection and response, which also helps in reducing the need for triggering the more resource expensive adaptive immunity with specialized defense mechanisms. Hence mapping the entire immune system provide a more holistic view which might give valuable insights in developing an adaptive and resilient maintenance framework.

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Table 1: Immune system based maintenance framework

Reference	Cells Involved	Immune mechanism	Framework/Approach	Use Case/Application
Dai et. al.,2011 [17]	Antibodies	Clonal selection algorithm	Dynamic time wrapping algorithm generated for known normal & fault samples	Penicillin fermentation process
Laurentys et. al.,2010 [12]	Not Specified	Negative selection & Danger Model	Decision making tool in dynamic system support with immune response triggered by alarms/dangerous signals	DC motor fault detection
Laurentys et. al.,2010 [18]	Dendritic* & Helper T-cell	Danger Model	Immune Danger Model for dynamic system fault detection	Actuator controlled water flow boiler
Huang et. al.,2002 [19]	Antibodies	Clonal selection algorithm	Affinity calculation to measure the combination intensity to prevent process stagnation	Taiwan Power System
Laurentys et. al.,2011 [13]	Natural killer cells	Natural killer cell activation & education	Zero sum balance mechanism in identifying the difference between normal and potential harmful activities	Actuator controlled water flow boiler
Bradley et. al.,2000 [20]	T cells	Negative selection	Self/non-self recognition in differentiating acceptable and abnormal states and transitions	Simulation using FPGA development board
Aydin et. al.,2012 [21]	Antibodies & memory cells	Negative selection	Affinity between antibody and antigen for fault classification by assigning antibody set for each class and applied to the model	Induction motor faults
Chilengue et. al.,2011 [22]	T-cells & B-cells	Negative selection	Dynamic detection of the pathogens followed by construction a characteristic image of machines operating condition	Stator and rotor circuits of induction machines
Ghosh et. al.,2011 [23]	T-cells & B-cells	Negative selection	Normal state samples (self) uses to develop a description of the non-self-space	Tank Reactor, Penicillin Cultivation, Distillation Column
Araujo et. al.,2003 [14]	T-cell & B-cell	Negative selection & Clonal selection	"Self" & "non-self" pattern recognition model for dynamic learning of product patterns	Gas lift oil well
Alizadeh et. al.,2017 [24]	Dendritic cell	Danger Model	Detection as well as isolation of sensor faults with a given dual sensor redundancy	Wind Turbine
Thumati et. al.,2012 [15]	T-cell & B-cell, memory cells	Negative selection & Memory capability	Online approximator in discrete-time (OLAD) in a fault detection (FD) observer	Axial piston pump
Chen et. al.,2010 [16]	B-cells, T-cells, Antibodies, Dendritic cells	Negative selection & Clone selection	Adaptive immune response with pattern recognition algorithm tuned to a certain type of structural damage pattern	Scaled steel bridge structure
Abid et. al.,2017 [25]	Antibodies$	Negative selection	feature extraction & selection with feature space transformation followed by optimization considering non-self feature space	Motor bearing fault detection
Alizadeh et. al.,2016 [26]	T-cells	Negative selection	Negative selection algorithm design for detection and isolation of common occurring faults	Wind Turbine

* - presented in the work as Antigen Presenting Cell, $ - T-Cells determines negative selection not antibodies

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2 Developed Frameworks

2.1 Self-configuration Framework

2.1.1 Vision and Assumptions

This chapter details the framework's implementation, covering its developmental assumptions and methodologies for machine configuration.

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 presumed to be single-component, each with predefined tasks based on their characteristics. This streamlines the production process for efficiency.
- Machines and Tools: All machines are stationary and equipped with their own tools, ensuring consistent quality and minimizing the need for extra equipment. The work does not involve jigs and fixtures for machining processes.
- Batch Size: The assumption of batch size one means individual production for each product, leading to a more specialized and personalized manufacturing process.
- Process Flow: Products follow a predetermined sequence of one or more sequential tasks based on their characteristics, ensuring consistency and efficiency in production.
- Intelligent Products: Products are intelligent, interacting with the production process and providing feedback for continuous improvement.

In essence, the developed manufacturing framework optimizes single-component product production through consistent product characteristics, specialized machinery, batch size one production, predetermined process flow, intelligent products, efficient material handling, and bypassing a process planning stage. These assumptions collectively result in a more efficient and streamlined production process, generating high-quality single-component products.

2.1.2 Multi-agent based representation

This framework needs various agents to establish the proposed control logic for achieving the desired autonomy and distributed design. Here is a list and description of such elements:

- Product Agent: This agent serves as a logical representation of the physical product. It has knowledge of the required manufacturing operations.
- Machine Monitoring Agent: This agent acts as a logical abstraction of the health status of individual machines, enabling the calculation of variables such as Remaining Useful Life.
- Machine Configuration Agent: This agent provides a logical abstraction of the specific parameters for configuring each machine. It interacts with individual machines to provide tailored configuration parameters based on the product's requirements.

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- Transport Agent: It serves as a logical abstraction of the shop floor's transport elements. This agent handles the transportation of raw materials to specific machines in accordance with the product's requirements.
- Collection Transport Group: Functioning as an element that acts as a directory, this component stores and manages relevant information regarding available transport agents.
- Collection Machine Group: Acting as a directory, this element stores and organizes pertinent information related to machine agents within the system.

The developed framework of this work is presented in Fig. 1.

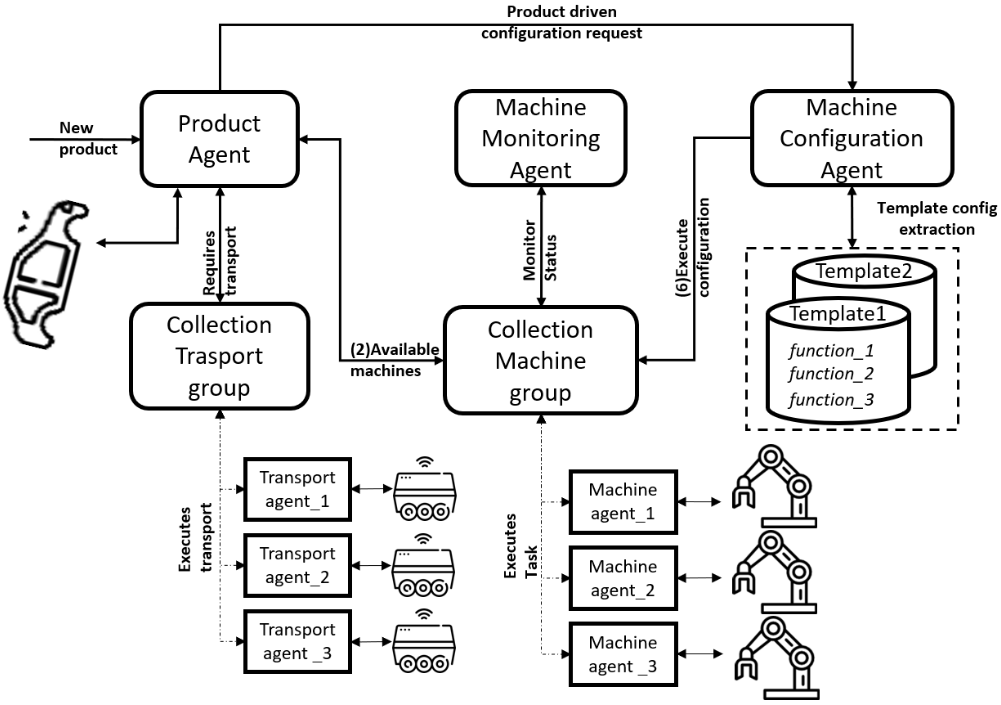

Figure 1: Multi-Agent based representation

2.1.3 Process flow representation (Product Agent)

The process flow depicts essential steps for assembly. It outlines tasks crucial for raw material execution, a complex modeling effort. Inspired by [27], we propose a streamlined representation, focusing on:

- *Process flow:* Contains necessary sequential information for product assembly, with at least one task.

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- *Task:* Represents fundamental assembly operations (e.g., picking and placing, screwing, welding), composed of finer process steps.
- *Process step:* Defined as an elementary operation in a process flow, indivisible into sub-steps [27]. Process steps form a functional robotic platform configuration, expressed through attributes (e.g., end effector movement, gripping).

Fig. 2(a) sketches a product's process flow and components. Fig. 2(b) details a process step's composition, showing examples like movement and gripping. Fig. 2(c) illustrates task sequences using process steps, like picking and placing and screwing.

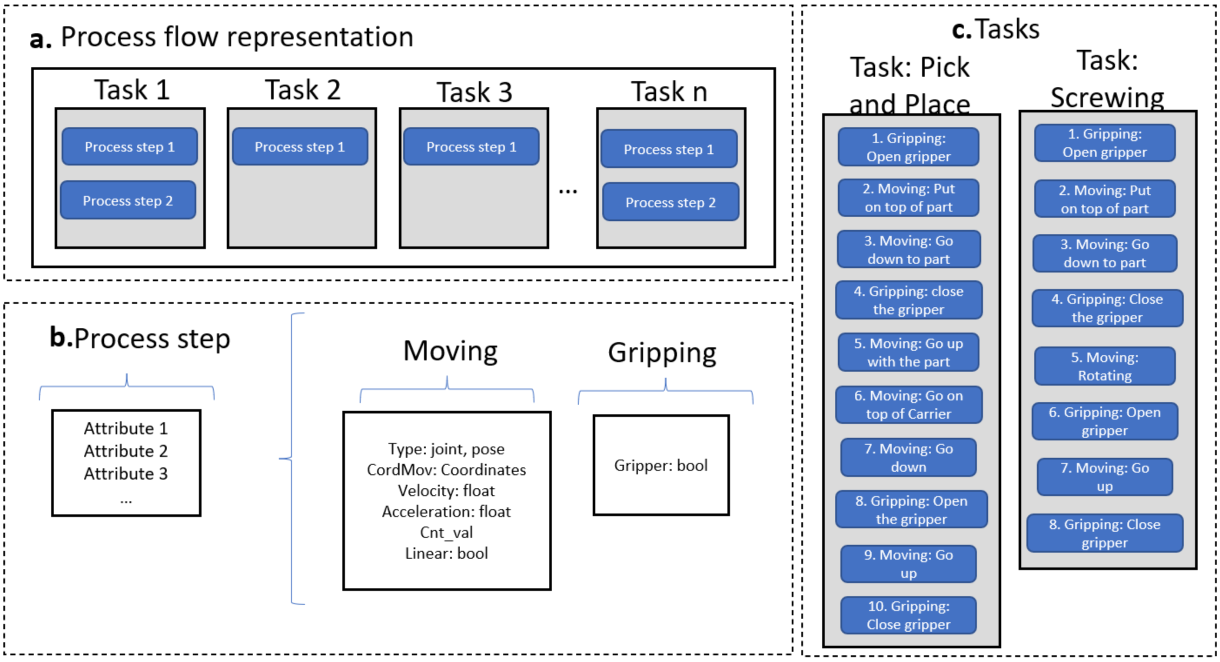

Figure 2: Process flow representation for machine self-configuration

2.1.4 Multi-agent based negotiation

The process logic starts with the launch of a new intelligent product. Each product entails at least one task, executed sequentially. Upon task initiation, it's routed to a machine group, which, based on available data, identifies suitable machine agents through a capability-matching process.

The optimal machine selection factors in availability, functional machine parameters, and their Remaining Useful Life (RUL). Each machine agent is linked to a monitoring agent, activating to return the calculated RUL.

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Following the identification of the machine with optimal parameters, the configuration agent is activated. This agent provides specific configuration parameters tailored to the product's requirements. Once the machine is configured, an available transport resource is selected to move the product to its subsequent location.

Within the workspace of the designated machine, the task is executed. Upon completion, the sequential process repeats for the next task until all tasks are performed. Figure 3 illustrates the logical sequence outlined in this paper.

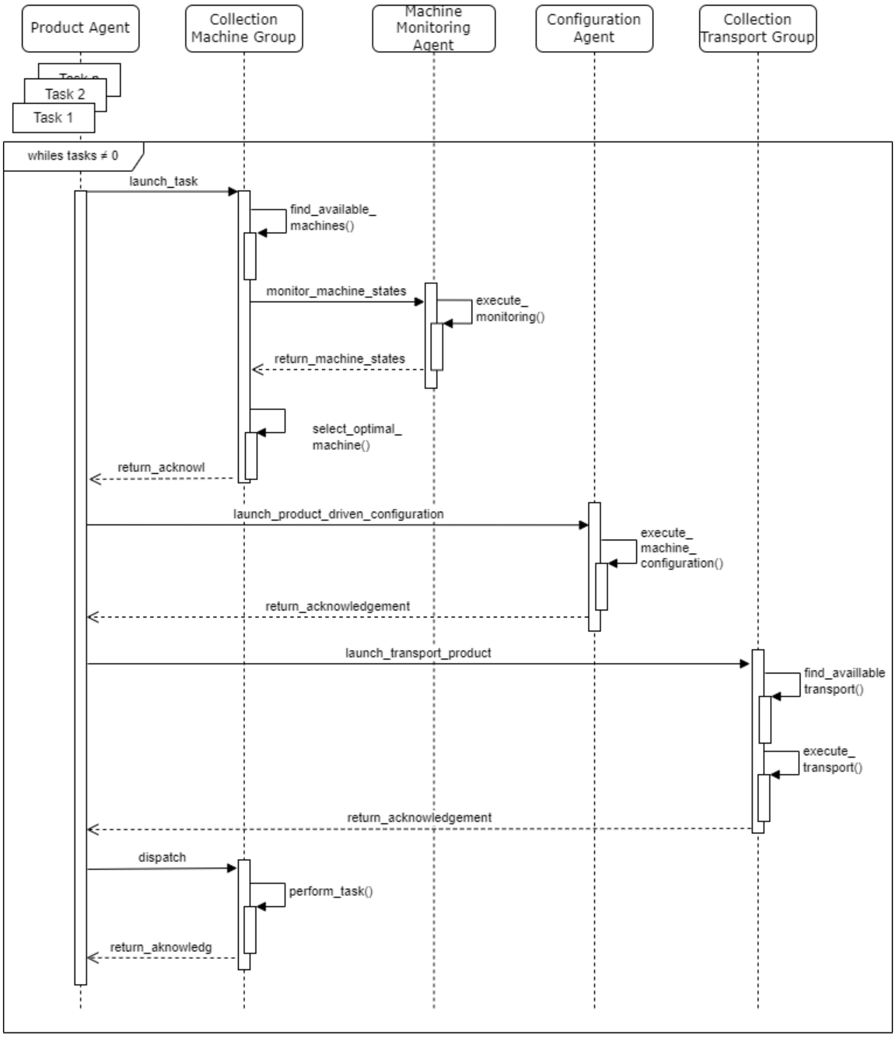

Figure 3: Multi-Agent based negotiation for machine self-configuration

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2.2 Self-diagnosis and self-monitoring Framework

A Self-diagnosis and Self-monitoring Framework draws parallels with the immune system and leverages emerging technologies to enhance efficiency and effectiveness. This framework is inspired by the immune system's ability to detect, respond, and adapt to abnormalities or threats within the body. Similarly, in manufacturing environments, the goal is to develop systems that can autonomously detect issues, predict potential failures, and optimize performance. Just as the immune system continuously monitors the body for signs of illness or dysfunction, the Self-diagnosis and Self-monitoring Framework continuously assesses the health and performance of manufacturing processes and equipment.

It mimics the immune system's ability to recognize and respond to anomalies swiftly. This framework utilizes cutting-edge technologies such as artificial intelligence, machine learning, Internet of Things (IoT), and big data analytics to gather data from various sensors and sources within the manufacturing environment. These technologies enable real-time monitoring, analysis, and decision-making, similar to how the immune system processes information from different parts of the body.

Drawing from the self-healing capabilities of the immune system, this framework emphasizes proactive and predictive maintenance strategies. By analyzing data patterns and historical performance, it can anticipate potential equipment failures or degradation and initiate maintenance actions before significant issues arise. This approach minimizes downtime, reduces costs, and optimizes productivity.

2.2.1 Immune system holistic view

Gaining a comprehensive understanding of the human immune system holds significant promise for informing the development of an immune-based maintenance framework. Ranked as the second most intricate system globally, following only the human brain, it is essential to provide a simplified overview of the immune system, focusing on key concepts crucial for crafting such a framework. The immune system functions to neutralize three primary types of disease-causing entities: parasitic worms, pathogens, and infected cells. In this overview, emphasis is placed specifically on the immune response against pathogens (refer to Fig. 4). It's worth noting that similar immune mechanisms are employed in combatting the other two types of disease cells. Each immune cell is assigned a primary task, accompanied by a maximum of three secondary responsibilities. For instance, macrophages are primarily tasked with pathogen elimination, while also possessing secondary roles in cell communication and activation of other immune cells [28].

- *Innate and Adaptive :* The human immune system oversees and preserves our well-being through various stages, employing a diverse array of cells for specific functions. It operates through two main types of immunity: Innate and Adaptive. Innate immunity, present since birth, employs general-purpose cells to combat a wide range of pathogens. On the other hand, Adaptive immunity utilizes specialized cells with targeted attacks against specific pathogens, exerting a profound impact on their designated targets.

- *Innate Immunity [28]:* The innate immune system acts as the body's initial defense mechanism against pathogens, operating from birth and providing a non-specific response. When pathogens invade, they rapidly multiply and alter their surroundings, triggering a response

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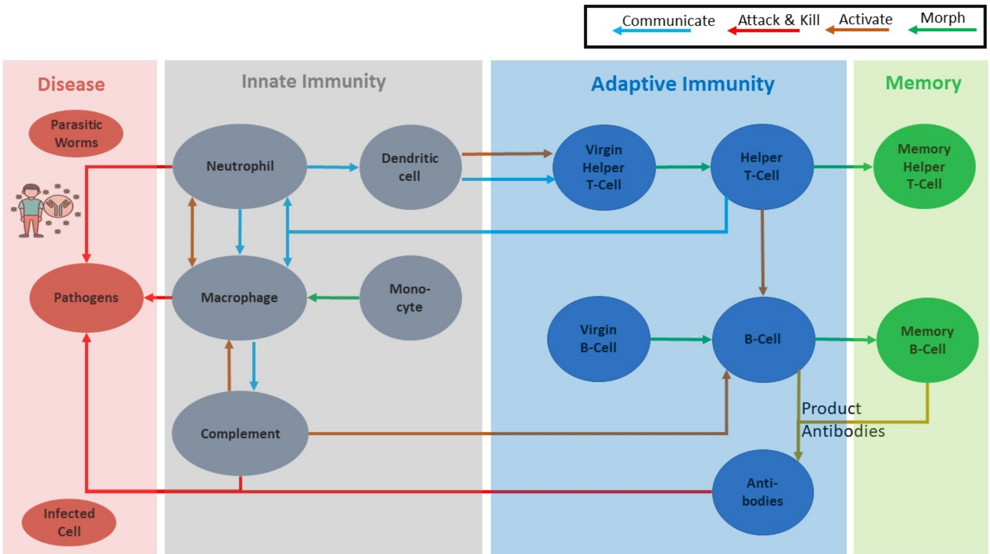

Figure 4: Innate and Adaptive Immune cells

from damaged cells which activate innate immune cells like Macrophages, Neutrophils, and complements. These cells work to neutralize the threat by engulfing invaders, trapping them, and breaking them down using enzymes or releasing toxins. Typically, innate immunity successfully combats attacks, but in the case of stronger pathogens, dendritic cells are mobilized to gather antigen samples and initiate the next stage of the immune response.

- *Adaptive Immunity [29, 30]:* Innate immunity is a broad and immediate defense mechanism present from birth, providing nonspecific protection against various pathogens. On the other hand, adaptive immunity is a more targeted response that develops over time upon exposure to specific pathogens. Dendritic cells in the lymph nodes activate helper T-cells, which then trigger a cascade of events, including the duplication of helper T-cells to support macrophages and the activation of specific B-cells. These activated B-cells produce antibodies that bind to pathogens, providing saturation and protection against their attack. Additionally, some T and B cells become memory cells, ensuring a quicker and more effective response upon encountering the same pathogen in the future.

- *Intelligence and Response:* The responsibilities of immune cells, encompassing both innate and adaptive immunity, can be categorized into two main functions: tasks related to gathering intelligence and tasks focused on generating responses.

- *Innate and Adaptive Intelligence [31, 32]:* Macrophages are pivotal in innate immunity, detecting distress signals like cytokines to prompt immune reactions, including recruiting neutrophils and complement proteins. They also signal their location and urgency and can summon dendritic cells to enhance adaptive immunity. Dendritic cells, after collecting

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antigens, trigger specific immune responses like anti-bacterial defenses and engage helper T cells to ensure precise immune reactions, preventing harm to healthy cells. Ultimately, helper T cells collaborate with B cells to execute targeted immune responses.

- *Innate and Adaptive Response [33]:* In the innate response, macrophages, large cells approximately 21mm in diameter, defend against invaders by engulfing up to 100 intruders, enclosing them within a membrane, and breaking them down with enzymes. They also induce inflammation by prompting blood vessels to release water into the infected area, while complement proteins disable bacteria by creating holes in their membranes. Neutrophils contribute by releasing toxins that form barriers to trap and kill bacteria, although they are subsequently eliminated to prevent harm to healthy cells. In the adaptive response, T-cells assist macrophages with chemical signals, while B-cells produce antibodies at a rate of around 2000 antibodies per second, saturating the battlefield to incapacitate bacteria and aid macrophage function.

- *Libraries and Memory Support [34, 28]:* Adaptive immune cells possess specialized capabilities to defend against existing and potential future diseases, facilitated through the processes of development, training, and storage within the Thymus, bone marrow, and lymph nodes. This intricate system utilizes a combination of gene segments to create a diverse array of proteins capable of recognizing virtually any protein encountered. Memory cells play a crucial role in providing enhanced protection upon subsequent encounters with familiar pathogens, thereby bolstering the immune response against future threats.

2.2.2 Immune system and emerging technologies

This section details the interconnection of current emerging technologies and their potential application in achieving the essential attributes of the immune system. Six crucial characteristics have been recognized, offering insights into the development of an intelligent maintenance system.

- *Ignorant but collaborative :* Immune cells have specific roles but lack centralized control, working collaboratively to keep the body safe. Their behavior resembles a multi-agent system, where each cell performs its task while also collaborating with others to achieve overall goals.

- *Federated system :* The immune system operates across various body locations, supported by a vast transport network of lymph vessels. The innate immune response operates at sites of damage, while adaptive immunity develops in lymph nodes. Achieving a federated system for immune function could involve Edge, Fog, and Cloud computing with decentralized control, along with the potential integration of IoT devices. (See Table 2)

- *Distributed Intelligence :* The text discusses the two types of intelligence in the immune system, innate and adaptive, and proposes the utilization of technologies like Ontologies and Machine Learning to achieve distributed intelligence. It refers to Table 1 for details on different tasks and their implementation using Machine Learning. (See Table 2)

- *Extensive Knowledge Base :* The adaptive immune system possesses a vast knowledge base enabling it to resist diseases past, present, and potentially future by connecting to all

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possible proteins in the universe. It retains memory of past attacks and defensive strategies throughout its lifespan. This extensive knowledge is acquired and managed through Big Data techniques, including data injection, storage, processing, and retrieval.

- *Intelligent Response System :* In the preceding section, we discussed the immune system's two main responses: innate and adaptive. These responses can be implemented across different areas of maintenance using Digital Twin for remote assistance and Augmented Reality (AR) for on-site support. For example, in tool condition monitoring, Digital Twin technology can facilitate adjustments to CNC machine parameters, while AR can assist maintenance personnel with tool replacement tasks.

- *Complex System :* The human immune system is incredibly complex, ranking second only to the human brain. While automation has progressed in computer systems, there's a need for human-centered AI approaches to manage the intricate nature of smart maintenance systems, particularly in decision-making areas where humans may need to collaborate with AI tools.

Table 2: Innate and Adaptive intelligence using Machine Learning and Cloud technologies

Task	**Cells**	**Innate / adaptive**	**Body Location**	**Machine Learning**	**Edge / Cloud**
Release & attract to cytokines	Macrophages	Innate	Damage site	Classification	Edge
Collect Antigen	Dendritic cell	Innate	Damage site	Feature Extraction	Edge
Activate the specific Virgin T-cell	Dendritic cell	Adaptive	Lymph nodes	Clustering Algorithm Selection	Cloud
Identify between body & bacteria cell	Helper T-cell	Adaptive	Lymph nodes	Labelling	Cloud
Activate the specific virgin B-cell	Helper T-cell	Adaptive	Lymph nodes	Classification Algorithm Selection	Cloud

2.2.3 Immune system-based Smart Maintenance Framework

The concept draws from the comprehensive understanding of the immune system and advancements in computer technology. We suggest a sophisticated maintenance approach for intricate shop-floor operations. This framework comprises four key modules: Physical Asset, Innate

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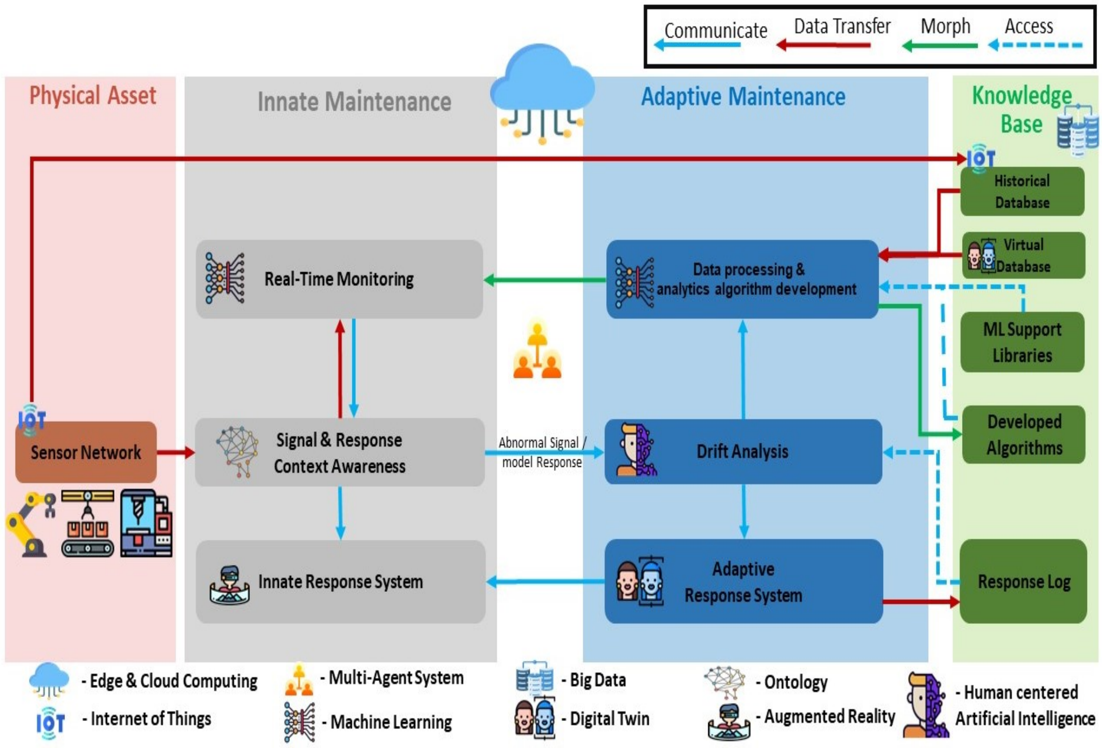

Figure 5: Immune based smart maintenance framework

Maintenance, Adaptive Maintenance, and Knowledge Base. Each module is composed of various components aimed at fulfilling specific functions (refer to Fig. 5).

Physical Asset: The physical asset discussed in this paper refers to machinery, equipment, or components requiring maintenance. Throughout the paper, these assets are collectively referred to as "machines." Additionally, it includes a network of sensors aimed at monitoring machines and collecting real-time data for maintenance purposes.

- *Sensor Network :*A sensor network is crucial for monitoring the real-time status of machines targeted for maintenance, with various sensors such as force, vibration, temperature, etc., being commonly used. Employing multiple sensors can enhance prediction accuracy. Key considerations during data acquisition include sensor placement, sampling frequency determination based on factors like sensor limitations and connection type, and implementing noise reduction techniques such as filtering.

- *Data acquisition:* The proposed framework allows for sensor data transmission in both wired and wireless formats. This data serves two purposes: real-time monitoring and response by the Innate maintenance system, and storage in a Knowledge base for future use in developing an adaptive model. The choice between wired and wireless transmission de-

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pends on the sampling frequency, with wireless transmission preferred for lower frequencies due to its simplicity and flexibility in sensor placement.

- *Internet of Things and Edge and Cloud Storage :* The sensors function akin to Internet of Things devices, transmitting data from the edge to cloud storage within the knowledge base. Additionally, local edge storage is essential to handle transmission disruptions and data loss effectively.

Innate Maintenance: Innate maintenance involves ongoing monitoring and immediate responses to machine issues, typically performed near the equipment.

- *Real-time monitoring :* The real-time monitoring of sensor data from the physical asset allows for the assessment of the machine's current state based on an established model. This process involves data processing and analytics algorithms created by adaptive maintenance. Predictions regarding the machine's condition are made and relayed to the context awareness block to determine necessary actions.
- *Machine Learning, Edge and Cloud computing :* Machine learning is used for data analytics, with adaptive maintenance deploying models for real-time machine condition prediction, necessitating care in addressing online prediction constraints, especially for edge deployment. Edge devices require high processing power to handle complex models, along with a parallel data storage system for cloud storage, considering potential data missing during online prediction and for future processing. Long-term model deployment requires consideration of data drift, suggesting updates to ensure adaptiveness and resilience.
- *Innate Response System :* The maintenance system offers rapid responses to machine needs, with online predictions enabling implementation of various response systems. Alarm signals notify operators of machine status, prompting adjustments or halting operations via control systems.
- *Augmented Reality :* Operators use augmented reality (AR) to perform maintenance tasks efficiently by following instructions relayed by an adaptive response system, enhancing their effectiveness in responding to alarm signals. AR assists operators by providing step-by-step instructions for carrying out maintenance activities, improving their ability to address current situations promptly.
- *Context Awareness :* A system analyzes sensor signals and responses prior to real-time monitoring. It focuses on detecting concept/data drift in signals and updating monitoring accordingly. It assesses response validity against expected outcomes, including Remaining Useful Life (RUL) calculations based on machine knowledge and operator expertise. Abnormal signals or responses prompt adaptive maintenance and potential updates to the real-time monitoring system for further analysis.
- *Multi-agent system and Ontology :* Ontologies facilitate sensor signal analysis and capture expert knowledge, enabling reasoned model responses. Within maintenance systems, individual blocks function as agents with specific tasks, communicating and collaborating with others to achieve collective objectives.

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Adaptive Maintenance: Adaptive maintenance involves detailed analysis and development of real-time monitoring algorithms, drift analysis, and responsive systems. It's typically conducted remotely from the physical asset to optimize maintenance activities. This approach enhances efficiency and responsiveness in managing maintenance needs.

- *Data processing and analytics algorithm development :* Develops algorithms for real-time machine monitoring using historical or virtual databases, involving steps like data cleaning, feature extraction, and labeling for model generation.
- *Data Cleaning :* Eliminates irrelevant data and handles missing values, crucial for maintaining accuracy during processing and analysis.
- *Feature Extraction :* Extracts features from data using techniques like time series analysis, statistical parameters, frequency domain analysis, and wavelet transform.
- *Labelling:* Groups data based on similarities through clustering, considering preprocessing, choice of clustering techniques, algorithm parameter selection, and performance evaluation.
- *Model Building, Evaluation and Deployment :* Develops classification models, selects appropriate techniques, controls parameters, and evaluates performance before deploying for real-time monitoring.
- *Drift Analysis :* dentifies distribution changes in signals, triggers necessary actions like algorithm initialization or adaptive response upon abnormality detection.
- *Human-centered AI :* Utilizes AI tools for data processing and visualization, allowing humans to make informed decisions regarding abnormality responses.
- *Adaptive response system :* Responds to maintenance needs based on concept or data drift, communicating with innate response systems and logging actions for future reference.
- *Digital Twin :* Utilizes advanced techniques like Digital Twin for real-time system monitoring and implementing necessary changes to system parameters.

Knowledge Base: To establish a smart maintenance system, it's essential to build a comprehensive knowledge repository comprising data, algorithms, and libraries to facilitate Adaptive maintenance. This entails harnessing Big Data technology for tasks like data injection, cloud storage, processing, and retrieval. The key elements of this repository include a Historical Database for storing sensor data, a Virtual Database for simulation data, Machine Learning Support Libraries for advanced algorithm development, and a log to record developed algorithms and their corresponding responses.

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3 Pilot and Validation

3.1 Self-configuration Framework - Pilot and Validation

3.1.1 Pilot description

The implemented use case involves software development for the self-configuration of a specific robotic platform. To demonstrate this, a simple product—a hinge—was selected. Hinges function to join two parts, creating a revolute joint between them.

This example comprises four main components: pin, inferior leaf (part C), superior leaf (part B), and a screw (part A). The objective of this assembly operation is to pick and place the inferior leaf, superior leaf, and screw onto the pin. Following the screw placement, a screwing operation is conducted. Refer to Fig. 6 for a 3D depiction of the parts and assembly process.

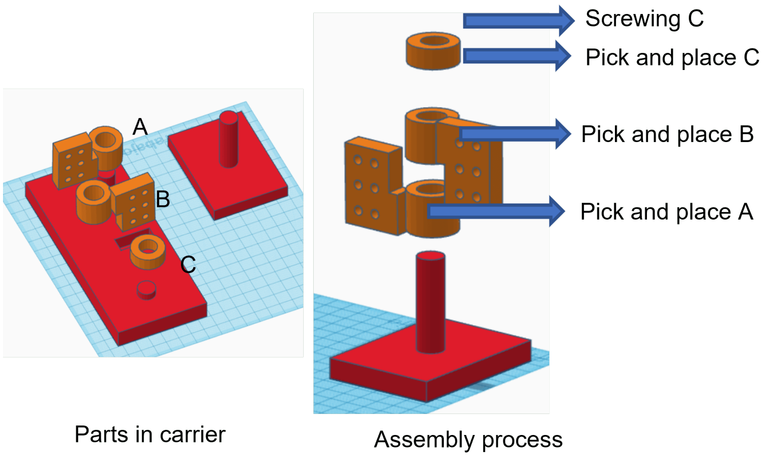

Figure 6: Sequential steps for the assembly of a hinge

3.1.2 Software implementation

The software implementation involved developing and integrating four Python scripts and a JSON file representing the assembly process flow. JSON was chosen for its simplicity in handling data. Other formats like AutomationML (AML) or Business to Manufacturing Markup Language (B2MML) could enhance interoperability and process standardization. The FANUC Educational cell (R-30iB Mate Plus Controller) is utilized robotic platform.

In this scenario, we presume that the Product Agent contains the JSON file (assembly process flow). When it is launched it sends this information to the Configuration Agent which will extract the parameters, tasks, and process steps. Also, it contains the Assembly templates which are related to the Robotic platform being used. The Configuration Agent will provide relevant configuration parameters to the Machine Agent. It has bidirectional communication with the Robotic platform. In summary, the scripts implements have the following characteristics:

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- *Extraction of Tasks, Process Steps, and Parameters:* Extracts crucial parameters from the recipe (JSON file).
- *Assembly Templates:* A set of functions representing pre-built sequences of steps.
- *FANUC Robotic Framework:* A script enabling connection and communication with the robotic framework. In this instance, the 'fanucpy' Python package for FANUC industrial robots was employed [35, 36]. This driver has undergone testing in KAREL and FANUC teach pendant languages. By establishing a connection with the robot controller server, it allows easy access to control and monitoring variables. It comes with predefined functions aiding in the movement, opening, and closing of the robotic platform's gripper (FANUC educational cell).
- *Platform Integration:* A script that integrates assembly parameters, templates, and communication framework to execute robot movements.

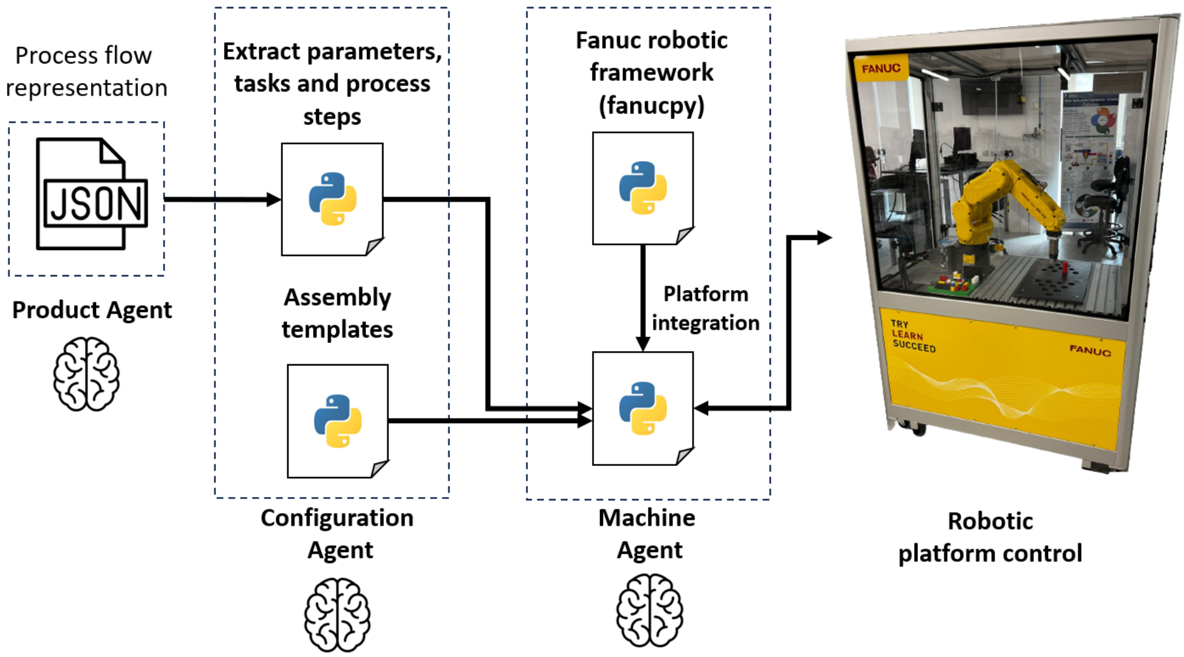

Figure 7: Software implementation of the system

Compared to Fig. 3, in the current pilot use case we have not implemented the Collection machine group nor the Machine Monitoring Agent. The use case is primarily focused on the configuration of a single robotic platform. Reason for overlooking the choice of a machine with optimum conditions.

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3.1.3 Results and discussion

Two JSON recipes were used to test the developed scripts: one for assembling the hinge and the other for disassembling it. The disassembly recipe, especially, promotes practicality by enabling reusability and recycling of products, allowing them to disassemble themselves.

Fig. 8.a illustrates the hinge assembly process, while Fig. 8.b depicts its disassembly post self-configuration using the FANUC educational cell.

In contrast to other research that relies on predefined skill sets or centralized servers managing parameters, this approach enables real-time self-configuration. This leads to significantly reduced configuration time and effort during the launch of new products. As long as the manufacturing resources possess the physical capabilities for an operation and access to templates, there's a considerable boost in production possibilities in terms of product variations.

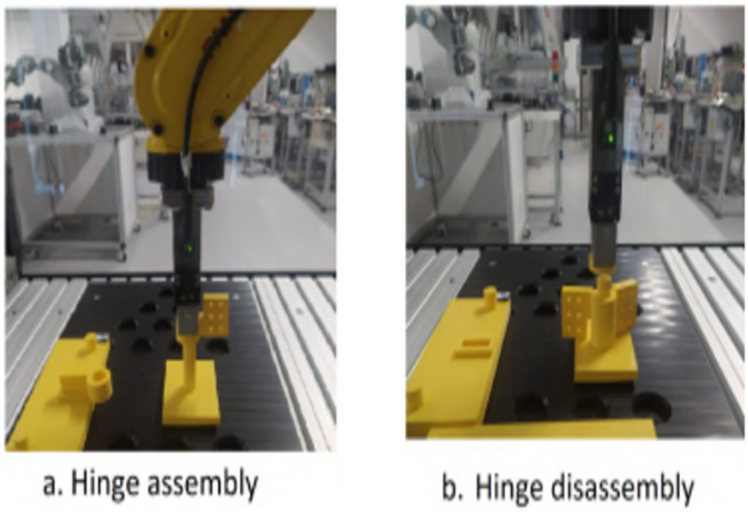

Figure 8: Implementation of the self-configuration framework using the FANUC educational cell in the (a) assembly and (b) disassembly of a hinge

3.2 Self-diagnosis and self-monitoring - Pilot and Validation

This section focuses on demonstrating the proposed framework for tool wear monitoring in a CNC milling machine (Fig-5). It presents a partial implementation using machine learning, one of the framework's mentioned technologies. This implementation utilizes three public datasets from the PHM 2010 Data Challenge.

The key aim here is to demonstrate the framework's applicability in tool wear monitoring, not to achieve the highest possible accuracy. As such, the implementation employs established machine learning algorithms for their accessibility and widespread use.

3.2.1 Pilot description

The workpiece was machined line-by-line, with the tool retracting between passes to complete layers. Experiments used a CNC milling machine to machine a steel workpiece under various parameters, collecting substantial sensor data. The process involved machining layers line-by-line with flank wear measurements. Table 3 provides experimental details, including sensors, equipment, and parameters, while Figure 9 illustrates sensor positions and wear measurements.

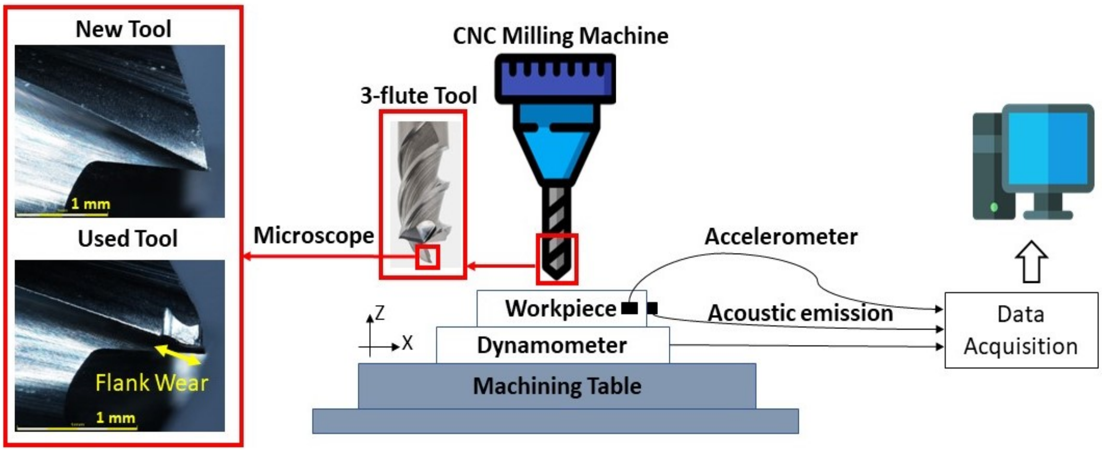

Figure 9: Experimental Setup (Setup adapted from [37], the tool wear image used was captured during an experimental campaign carried out at University of Nottingham)

3.2.2 Tool Wear Monitoring Framework

The tool wear monitoring system implements selected components of our proposed framework, including the Physical Asset, Innate Maintenance, Adaptive Maintenance, and Knowledge Base modules. While a full realization would incorporate every block in the immune-inspired smart maintenance framework, this use case involves a limited subset. The adapted framework for this tool wear monitoring application only includes chosen elements of the modules, as depicted in 10. By focusing on key components like data acquisition, feature extraction, training classification models, and predictive analytics, this case study demonstrates applying the core modules of the framework to a targeted predictive maintenance scenario.

*Physical Asset:*The physical asset includes a 3-axis CNC milling machine equipped with various motion control units like position sensors, rotary encoders, proximity switches, current sensors, and pressure sensors. Additionally, three types of external sensors were added: a 3-axis dynamometer for cutting force measurement, three accelerometers for detecting vibrations in the X, Y, and Z directions, and an Acoustic Emission (AE) sensor for monitoring stress waves from the cutting process. The accelerometers and AE sensor were attached to the side of the workpiece, while the dynamometer was positioned between the workpiece and the machining table.

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Table 3: Experimental Setup

Milling Machine Setup	
CNC milling machine	Röders Tech RFM760 (3-axis high speed)
Workpiece	Flat stainless steel workpiece (HRC52)
Tool	6mm 3 flute cutter ball nose WC cutter
Machining Parameters	
Number of Experiments	3
Spindle speed	23,600 rpm
cutting speed	4.7 m/min
Z-depth of cut (axial depth)	0.2 mm
Y-depth of cut (radial depth)	0.125 mm
Cutting time	15 s/pass
Pass length	108 mm
Number of passes/layer	252
Cutting distance	27,216 mm/layer
Number of layers	315
Sensors and Measurement Equipment	
Tool wear measurement	LEICA MZ12 microscope
Force Sensors	Kistler 3-component platform dynamometer
Vibration Sensors	3 Kistler piezo accelerometer
Acoustic Emission Sensor	Kistler Acoustic emission sensor
Measurement parameters	
sampling rate	50 kHz/channel
Number of signal channel	7 (F_x,F_y,F_z,Vib_x,Vib_y,Vib_z,AE)
Data size	3.2 GB/experiment

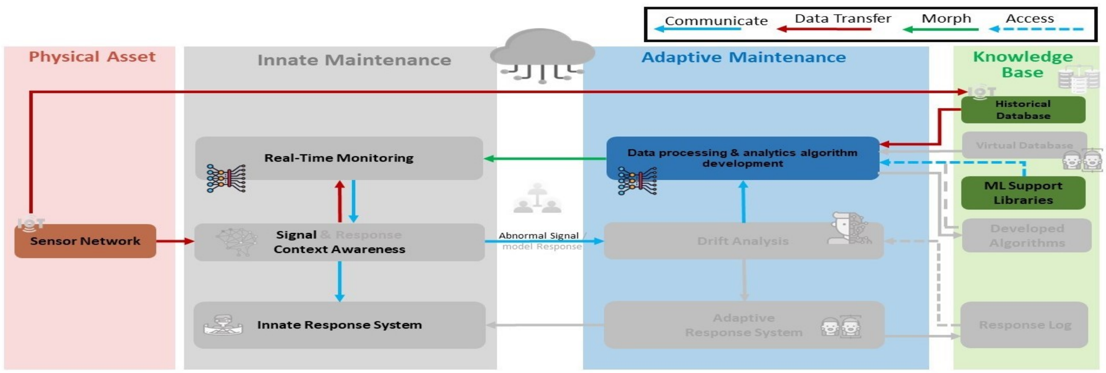

Figure 10: Tool Wear Monitoring Framework adapted from the immune-based smart maintenance framework (The block faded in grey color are not used/developed for this use-case)

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The optimal sensor arrangement for this experiment was determined based on sensor performance and their compatibility with data processing and analysis algorithms (Table-9). Sensor outputs, such as cutting forces, are initially captured as charges, then converted to voltages via charge amplifiers. This sensor data is stored in a historical database to refine data processing and analytics algorithms and is also used for real-time monitoring of tool wear conditions.

Table 4: Sensor selection based on clustering data

Sensor	**Clustering Algorithm**	**Exp-1 Score***	**Exp-2 Score***	**Exp-3 Score***
Force, Vibration & Acoustic Emission	Agglomerative	64.7	80.9	52.7
	Birch	66.8	70.5	60.1
	KMeans	45.4	76.0	60.2
	Gaussian Mixture	55.4	28.4	65.9
Force and Vibration	Agglomerative	37.5	70.5	89.2
	Birch	60.1	70.5	63.4
	KMeans	46.4	81.1	60.2
	Gaussian Mixture	59.3	56.3	61.5
Only Force	Agglomerative	66.4	47.9	63.4
	Birch	81.6	75.5	75.1
	KMeans	63.8	76.0	82.9
	Gaussian Mixture	63.7	94.6	85.8
Only Vibration	Agglomerative	41.4	85.4	55.2
	Birch	41.4	86.2	89.2
	KMeans	41.4	99.3	55.2
	Gaussian Mixture	28.1	54.4	17.7
Only Acoustic Emission	Agglomerative	1.3	3.5	0.9
	Birch	2.5	8.1	2.6
	KMeans	1.7	3.5	0.9
	Gaussian Mixture	0.8	3.8	0.6

The results presented here are considering RMS as Feature Selection
-Normalized mutual information score

*Innate Maintenance:*This module has three parts - to check the sensor data and to act based on the tool wear. Only the "Real-time monitoring" part was done in this case. The other two parts are ideas for the future. The module has three parts:

- Real-time monitoring: This part uses a model to check the sensor data and detect the tool wear. A model is a mathematical formula that can predict the tool wear based on the sensor data. The sensor data is the information that the sensors collect from the machine, such as the speed, the feed, the depth of cut, the temperature, the vibration, etc. The model was made using one set of sensor data and tested using two other sets of sensor data. The model works well, but there is a small delay and some data loss when it runs 11.

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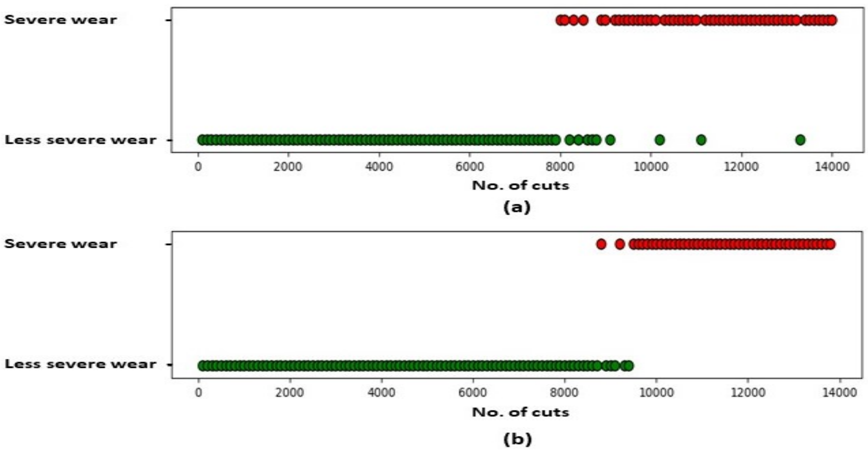

Figure 11: Innate intelligence tool wear monitoring results (Online tool wear monitoring using Logistic Regression model developed using exp-1 as historical data and tested using data from (a) Exp-2 (b) Exp-3)

- Signal Context Awareness: This part makes sure that the model is suitable for the current machine settings. The machine settings are the values that control how the machine operates, such as the speed, the feed, the depth of cut, etc. If the machine settings change a lot, the model might not work well anymore. For example, if the speed is much lower, the tool wear might be different. In that case, this part makes a new model using the old or simulated data for the new machine settings. The old data is the sensor data that was collected before. The simulated data is the sensor data that was generated by a computer program. The new model replaces the old model in real-time monitoring.
- Innate Response system:This part of the module has different ways of dealing with severe tool wear. Severe tool wear is when the tool is very worn out or damaged from cutting the material. This can make the product worse or the machine unsafe. Depending on the situation, this part can do one of these things: warn the operator with a signal or a message, change the machine settings like speed, feed, or depth of cut, control the coolant that cools the tool or the material, or stop the machine to avoid more damage.

Adaptive Maintenance: Adaptive maintenance is a set of steps for creating and using machine learning models. Machine learning models are formulas that can learn from data and make predictions. Figure 12 shows the different steps of making and testing the formulas. The data is the information that comes from the sensors on the machine. The data does not have labels, which are the answers that the formulas need to learn. The current case focuses on the data preparation step, which is making the data ready for the formulas. This step uses a semi-automatic labeling technique, which is a way of giving labels to the data with some human help.

- Data Cleaning: The process begins by filtering out noise through a joint time-frequency distribution algorithm. Subsequently, signals associated with non-cutting activities are ex-

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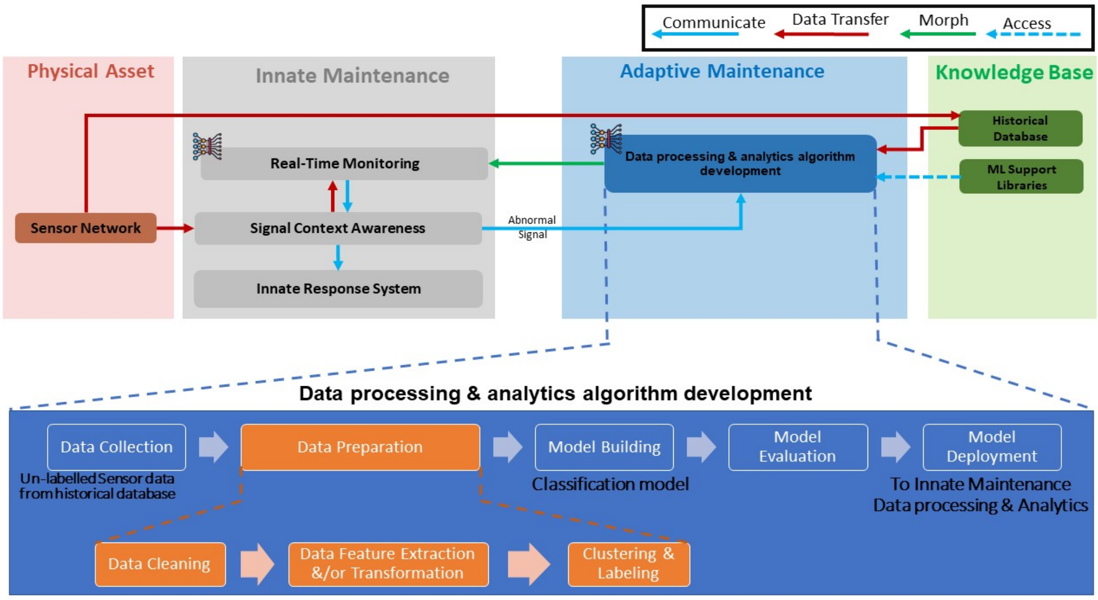

Figure 12: Data processing and analytics algorithm development

cluded by discarding data that exhibits forces below 5 Newtons. The outcomes of removing these non-cutting signals are detailed in Table-5.

- Feature Extraction: The data is a series of numbers that change over time. The data shows how the tool wears out when it cuts 315 layers of material. Each layer has about 220,000 numbers in the data. Using one number to summarize so many numbers might not be accurate. So, each layer of data was split into smaller parts of 5000 numbers each. Then, one number was calculated for each part. The number was based on some math formulas that describe the data, such as the root mean square, the peak value, and the average. These formulas are called statistical parameters. Many studies have used these formulas to get good numbers for predicting tool wear [38]. Table-8 shows how different formulas affect the prediction.

- Clustering: The data has 7 variables that are important for grouping the data. The data was prepared by changing the values of the variables to be between 0 and 1. This is called feature scaling. Then, 4 methods were used to group the data into 3 groups. The methods are called Agglomerative, Birch, KMeans, and Gaussian Mixture. There are different ways of finding the best groups for the data. The groups are based on the information in the knowledge base. The knowledge base is a collection of facts and rules about the data. The best method for grouping the data was selected and used for the next steps. The number of groups was 3 because the tool has 3 stages of wear. The stages are break-in, steady wear, and severe wear. They show how the tool changes over time. Table 7 and Figure 14

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have more details about the data and the groups.

- Labelling: The data was grouped into 3 clusters based on tool wear. The first time the third cluster appeared was at the start of severe wear. The data before that was called less severe wear (Value 0) and the data after that was called severe wear (Value 1). The tool wear was also checked after each layer by looking at the three edges of the tool. The highest wear value of the three edges was the tool wear (V_b) (Figure 14). The change in the angle of the wear was used to find the stages of the wear. To see how well the grouping worked, the wear was used as the true value. The wear was split into two groups: less severe wear and severe wear. The break-in group was not useful for the operator. Figure 13 shows the estimated severe wear and the true severe wear. The goal of the grouping was to make the estimated severe wear close to the true severe wear. A score called normalized mutual information could also be used to compare the true and estimated severe wear for each grouping method. This could help in choosing the best variables (Table 8) and sensors (Table 9) for the data.

- Model Building, Evaluation, and Deployment:The data was split into two groups based on the tool wear. A model was made to guess the tool wear group from the data. A model is a formula that can learn from the data and make predictions. Five different methods were used to make the model. The methods are called Logistic Regression, Multinominal Naive Bayes, Linear Support Vector, K-nearest Neighbors, and Decision Tree. There are different ways of finding the best formula for the data. The data was based on the information in the knowledge base. The knowledge base is a collection of facts and rules about the data. The best model was used for the next steps. The data came from three similar tests. The model was trained with one test data and tested with the other two test data. The model was scored based on how well it guessed the tool wear group. The scores were used to pick the best model (Table 10).

Table 5: Effect of filtering non-cutting signals

Clustering Algorithm	**7 input variable**		**Only force variable**	
	Raw Score*	Filtered Score*	Raw Score*	Filtered Score*
Agglomerative	53.9	95.5	64.3	64.9
Birch	56.5	80.1	62.9	83.2
KMeans	56.5	55.2	71.8	82.3
Gaussian Mixture	10.2	23.4	84.1	81.7

Note: The results presented here are considering peak value feature extraction
Experiment-3 data were used
Similar results could be found for other feature extractions/experiments)
*-Normalized mutual information score

*Knowledge Base:*The sensor data comes from the machine that is being monitored. The knowledge base also has some machine learning algorithms and other tools that are needed to

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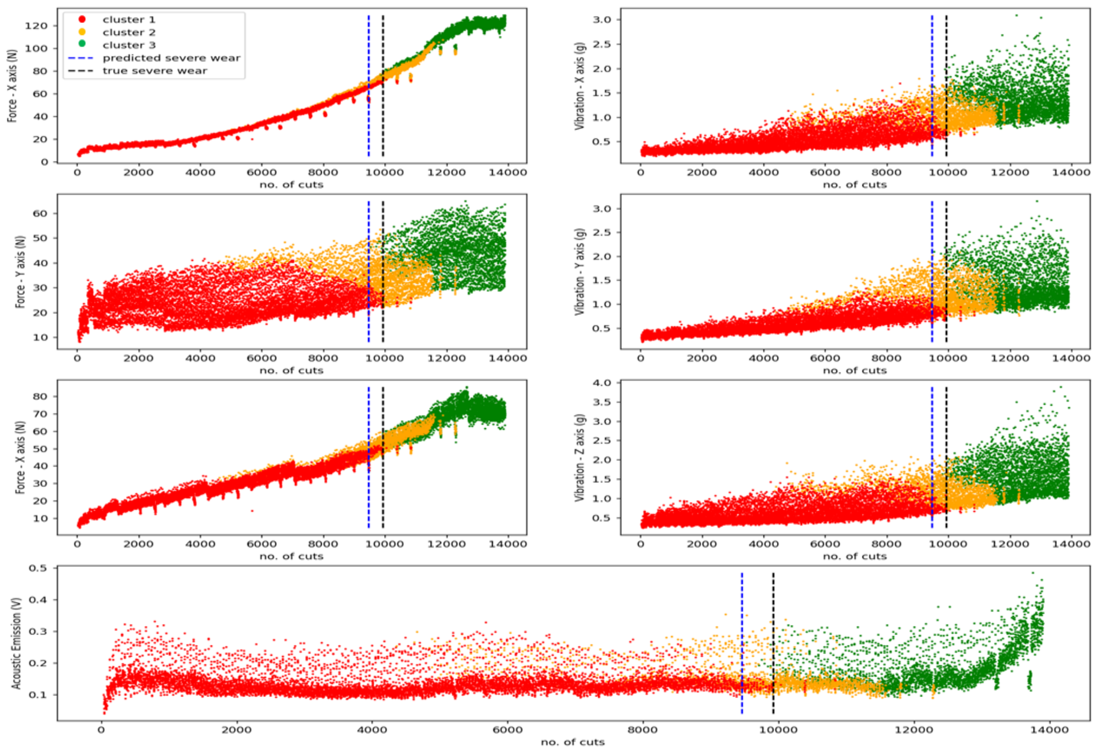

Figure 13: Semi-auto labelling of the peak values of each cut for Experiment-1

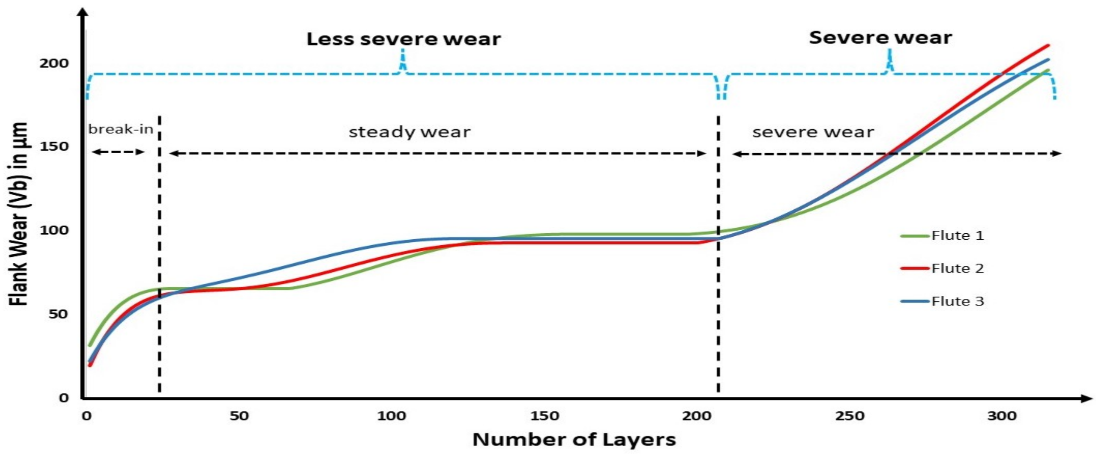

Figure 14: Flank wear on 3-flutes showing the three stages tool wear - break-in, steady and severe wear (results for measurement carried out for Exp-2)

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Table 6: Feature selection based on Clustering data

Features	**Clustering Algorithm**	**Exp-1 Score***	**Exp-2 Score***	**Exp-3 Score***	**Average** $\pm SD^{\ddagger}$
Peak Value	Agglomerative	39.6	49.5	95.5	61.5 ± 24.3
	Birch	39.6	63.2	80.1	61.0 ± 16.6
	KMeans	44.3	70.5	55.3	56.7 ± 10.7
	Gaussian Mixture	11.9	23.2	23.4	19.5 ± 5.4
Mean Value	Agglomerative	61.9	66.4	65.0	64.4 ± 1.9
	Birch	67.6	54.4	54.0	58.6 ± 6.3
	KMeans	70.1	57.0	76.2	67.8 ± 8.0
	Gaussian Mixture	61.9	49.5	76.5	62.6 ± 11.0
Root Mean Square (RMS)	Agglomerative	64.7	80.9	52.7	66.1 ± 11.6
	Birch	66.8	70.5	60.1	65.8 ± 4.3
	KMeans	45.4	76.0	60.2	60.5 ± 12.5
	Gaussian Mixture	55.4	28.4	65.9	49.9 ± 15.8

Note: The results presented here are considering all 7 input variables (F_x,F_y,F_z,Vib_x,Vib_y,Vib_z,AE)

$\star$-Normalized mutual information score ‡-Standard Deviation

Table 7: Clustering input variables and parameters

Input Variable	
Cutting force in the X-dimension	F_x (N)
Cutting force in the Y-dimension	F_y (N)
Cutting force in the Z-dimension	F_z (N)
Vibration in the X-dimension	Vib_x (g)
Vibration in the Y-dimension	Vib_y (g)
Vibration in the Z-dimension	Vib_z (g)
Acoustic Emission	AE (V)
Number of training set	
Experiment-1	13847
Experiment-2	14065
Experiment-3	13812
Number of Clusters	3

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Table 8: Feature selection based on Clustering data

Features	Clustering Algorithm	Exp-1 Score*	Exp-2 Score*	Exp-3 Score*	Average $\pm SD^{\ddagger}$
Peak Value	Agglomerative	39.6	49.5	95.5	61.5 ± 24.3
	Birch	39.6	63.2	80.1	61.0 ± 16.6
	KMeans	44.3	70.5	55.3	56.7 ± 10.7
	Gaussian Mixture	11.9	23.2	23.4	19.5 ± 5.4
Mean Value	Agglomerative	61.9	66.4	65.0	64.4 ± 1.9
	Birch	67.6	54.4	54.0	58.6 ± 6.3
	KMeans	70.1	57.0	76.2	67.8 ± 8.0
	Gaussian Mixture	61.9	49.5	76.5	62.6 ± 11.0
Root Mean Square (RMS)	Agglomerative	64.7	80.9	52.7	66.1 ± 11.6
	Birch	66.8	70.5	60.1	65.8 ± 4.3
	KMeans	45.4	76.0	60.2	60.5 ± 12.5
	Gaussian Mixture	55.4	28.4	65.9	49.9 ± 15.8

Note: The results presented here are considering all 7 input variables (F_x,F_y,F_z,Vib_x,Vib_y,Vib_z,AE)

$\star$-Normalized mutual information score ‡-Standard Deviation

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Table 9: Sensor selection based on clustering data

Sensor	Clustering Algorithm	Exp-1 Score*	Exp-2 Score*	Exp-3 Score*
Force, Vibration & Acoustic Emission	Agglomerative	64.7	80.9	52.7
	Birch	66.8	70.5	60.1
	KMeans	45.4	76.0	60.2
	Gaussian Mixture	55.4	28.4	65.9
Force and Vibration	Agglomerative	37.5	70.5	89.2
	Birch	60.1	70.5	63.4
	KMeans	46.4	81.1	60.2
	Gaussian Mixture	59.3	56.3	61.5
Only Force	Agglomerative	66.4	47.9	63.4
	Birch	81.6	75.5	75.1
	KMeans	63.8	76.0	82.9
	Gaussian Mixture	63.7	94.6	85.8
Only Vibration	Agglomerative	41.4	85.4	55.2
	Birch	41.4	86.2	89.2
	KMeans	41.4	99.3	55.2
	Gaussian Mixture	28.1	54.4	17.7
Only Acoustic Emission	Agglomerative	1.3	3.5	0.9
	Birch	2.5	8.1	2.6
	KMeans	1.7	3.5	0.9
	Gaussian Mixture	0.8	3.8	0.6

The results presented here are considering RMS as Feature Selection
-Normalized mutual information score

Table 10: Classification model score for various algorithms

Classification Algorithm	Exp-1 Training set		Exp-2 Training set		Exp-3 Training set		Average ± SD‡
	Exp-2 Test score*	Exp-3 Test score*	Exp-1 Test score*	Exp-3 Test score*	Exp-1 Test score*	Exp-2 Test score*	
Logistic Regression	88.44	93.78	76.46	95.82	90.34	91.78	89.44 ± 6.3
Multinominal Naive Bayes	71.53	71.84	78.80	71.84	78.80	71.53	74.06 ± 3.4
Linear Support Vector	71.53	71.84	78.80	71.84	78.60	93.55	77.69 ± 7.7
k-nearest neighbors	68.39	66.60	78.41	94.40	90.72	92.09	81.77 ± 11.3
Decision Tree	73.96	81.15	76.33	93.32	86.47	92.69	83.99 ± 7.5

Note: The results presented here are considering RMS as feature selection and using Birch clustering
⋆-Normalized mutual information score ‡-Standard Deviation

make and test the formulas for the data. The formulas are called data processing and analytics algorithms. They are used to understand and predict the tool wear.

3.2.3 Discussion

Our tool wear monitoring framework adapts key aspects of the proposed immune-inspired smart maintenance system by utilizing machine learning. Leveraging sensor data from the historical database, data processing, and analytics algorithms are developed.

Standard machine learning libraries accessed from the knowledge base guide data preparation. After cleaning non-cutting signals, the root mean square is extracted as the key feature. Birch clustering provides ideal labeling before training classification models. Logistic regression is chosen as the most accurate model for real-time monitoring.

For online monitoring, the analytics algorithm classifies and labels incoming sensor data to predict tool wear. The context awareness module analyzes the classification outputs, triggering tool changes when needed. Model accuracy is constantly tracked, and any major deviations trigger the re-development of the algorithm by the adaptive maintenance system. By considering updated data and advanced methods, it develops a more accurate and resilient model before accuracy deteriorates severely.

This use case attempts to demonstrate a smart maintenance framework incorporating resilience and anti-fragility by synergizing innate and adaptive capabilities. The system adapts to changes through context-aware, needs-based model refinement.

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4 Conclusion

This report introduces two innovative frameworks for manufacturing: a smart maintenance framework inspired by the human immune system and a manufacturing self-configuration framework. The smart maintenance framework integrates immune system characteristics with emerging technologies for comprehensive maintenance management. Pilot cases, like tool condition monitoring of a CNC milling machine, demonstrate its practicality. Future research will explore additional technologies like cloud computing and validate the framework across various scenarios.

Similarly, the manufacturing self-configuration framework streamlines robotic platform operation, eliminating the need for task-specific programming. Pilot cases, such as hinge assembly and disassembly, show its effectiveness. Future efforts will expand capabilities and integrate complementary technologies to maximize utility in manufacturing. These frameworks mark significant advancements in smart manufacturing, enhancing efficiency and adaptability in industrial processes.

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References

[1] Hamood Ur Rehman et al. "A Framework for Self-configuration in Manufacturing Production Systems". In: *Doctoral Conference on Computing, Electrical and Industrial Systems.* Springer. 2021, pp. 71–79.

[2] Stefan Scheifele et al. "Flexible, self-configuring control system for a modular production system". In: *Procedia Technology* 15 (2014), pp. 398–405.

[3] Hao Tang et al. "CASOA: an architecture for agent-based manufacturing system in the context of industry 4.0". In: *IEEE Access* 6 (2017), pp. 12746–12754.

[4] Mauro Onori et al. "The IDEAS project: plug & produce at shop-floor level". In: *Assembly automation* (2012).

[5] Regina Frei and Giovanna Di Marzo Serugendo. "Self-organizing assembly systems". In: *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 41.6 (2011), pp. 885–897.

[6] George Rzevski et al. "Ontology-driven multi-agent engine for real time adaptive scheduling". In: *2018 International Conference on Control, Artificial Intelligence, Robotics & Optimization (ICCAIRO).* IEEE. 2018, pp. 14–22.

[7] Andre Dionisio Rocha et al. "Agent-based plug and produce cyber-physical production system–test case". In: *2019 IEEE 17th International Conference on Industrial Informatics (INDIN).* Vol. 1. IEEE. 2019, pp. 1545–1551.

[8] Yingfeng Zhang et al. "Agent and cyber-physical system based self-organizing and self-adaptive intelligent shopfloor". In: *IEEE Transactions on Industrial Informatics* 13.2 (2016), pp. 737–747.

[9] Duncan McFarlane et al. "The intelligent product in manufacturing control and management". In: *IFAC Proceedings Volumes* 35.1 (2002), pp. 49–54.

[10] KUKA. "Matrix production: an example for Industrie 4.0". In: (2019).

[11] Terrin Pulikottil, Luis A Estrada-Jimenez, and Jose Barata. "Conceptual framework for smart maintenance based on distributed intelligence". In: *IFAC-PapersOnLine* 55.19 (2022), pp. 121–126.

[12] CA Laurentys et al. "Design of an artificial immune system for fault detection: a negative selection approach". In: *Expert Systems with Applications* 37.7 (2010), pp. 5507–5513.

[13] CA Laurentys, Reinaldo M Palhares, and Walmir M Caminhas. "A novel artificial immune system for fault behavior detection". In: *Expert Systems with Applications* 38.6 (2011), pp. 6957–6966.

[14] Mariana Araujo, Jose Aguilar, and Hugo Aponte. "Fault detection system in gas lift well based on artificial immune system". In: *Proceedings of the International Joint Conference on Neural Networks, 2003.* Vol. 3. IEEE. 2003, pp. 1673–1677.

[15] Balaje T Thumati, Gary R Halligan, and Sarangapani Jagannathan. "A novel fault diagnostics and prediction scheme using a nonlinear observer with artificial immune system as an online approximator". In: *IEEE Transactions on Control Systems Technology* 21.3 (2012), pp. 569–578.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant No. 814078

[16] Bo Chen. "Agent-based artificial immune system approach for adaptive damage detection in monitoring networks". In: *Journal of Network and Computer Applications* 33.6 (2010), pp. 633–645.

[17] Yiyang Dai and Jinsong Zhao. "Fault diagnosis of batch chemical processes using a dynamic time warping (DTW)-based artificial immune system". In: *Industrial & Engineering Chemistry Research* 50.8 (2011), pp. 4534–4544.

[18] CA Laurentys, Reinaldo M Palhares, and Walmir M Caminhas. "Design of an artificial immune system based on danger model for fault detection". In: *Expert Systems with Applications* 37.7 (2010), pp. 5145–5152.

[19] Shyh-Jier Huang. "Application of immune-based optimization method for fault-section estimation in a distribution system". In: *IEEE transactions on power delivery* 17.3 (2002), pp. 779–784.

[20] Daryl W Bradley and Andrew M Tyrrell. "Immunotronics: Hardware fault tolerance inspired by the immune system". In: *International Conference on Evolvable Systems*. Springer. 2000, pp. 11–20.

[21] Ilhan Aydin, Mehmet Karakose, and Erhan Akin. "An adaptive artificial immune system for fault classification". In: *Journal of Intelligent Manufacturing* 23.5 (2012), pp. 1489–1499.

[22] Z Chilengue, JA Dente, and PJ Costa Branco. "An artificial immune system approach for fault detection in the stator and rotor circuits of induction machines". In: *Electric power systems research* 81.1 (2011), pp. 158–169.

[23] Kaushik Ghosh and Rajagopalan Srinivasan. "Immune-system-inspired approach to process monitoring and fault diagnosis". In: *Industrial & engineering chemistry research* 50.3 (2011), pp. 1637–1651.

[24] Esmaeil Alizadeh, Nader Meskin, and Khashayar Khorasani. "A dendritic cell immune system inspired scheme for sensor fault detection and isolation of wind turbines". In: *IEEE Transactions on Industrial Informatics* 14.2 (2017), pp. 545–555.

[25] Anam Abid, Muhammad Tahir Khan, and Muhammad Salman Khan. "Multidomain features-based GA optimized artificial immune system for bearing fault detection". In: *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 50.1 (2017), pp. 348–359.

[26] Esmaeil Alizadeh, Nader Meskin, and Khashayar Khorasani. "A negative selection immune system inspired methodology for fault diagnosis of wind turbines". In: *IEEE transactions on cybernetics* 47.11 (2016), pp. 3799–3813.

[27] Veit Hammerstingl and Gunther Reinhart. *Skills in Assembly*. Version 1.1. 2018.

[28] Philipp Dettmer. *Immune - A journey into the mysterious system that keeps you alive*. 1st ed. Carmelite House, 50 Victoria Embankment, London EC4Y 0DZ: Hodder & Stoughton Ltd, 2021.

[29] Leandro N de Castro and Jon Timmis. "Artificial immune systems: a novel approach to pattern recognition". In: *Kent Academic Repository* (2002).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant No. 814078

[30] R Deaton et al. “A DNA based artificial immune system for self-nonself discrimination”. In: *1997 IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation*. Vol. 1. IEEE. 1997, pp. 862–866.

[31] Stephanie Forrest et al. “Self-nonself discrimination in a computer”. In: *Proceedings of 1994 IEEE computer society symposium on research in security and privacy*. Ieee. 1994, pp. 202–212.

[32] Leandro Nunes De Castro. *Fundamentals of natural computing: basic concepts, algorithms, and applications*. Chapman and Hall/CRC, 2006.

[33] Niels Kaj Jerne. “The immune system”. In: *Scientific American* 229.1 (1973), pp. 52–63.

[34] Yanfei Zhong et al. “An unsupervised artificial immune classifier for multi/hyperspectral remote sensing imagery”. In: *IEEE Transactions on Geoscience and Remote Sensing* 44.2 (2006), pp. 420–431.

[35] Agajan Torayeff. *fanucpy: Python package for FANUC industrial robots*. Version 0.1.5. 2022.

[36] Agajan Torayev et al. “Towards Modular and Plug-and-Produce Manufacturing Apps”. In: (2022).

[37] Giovanna Martínez-Arellano, German Terrazas, and Svetan Ratchev. “Tool wear classification using time series imaging and deep learning”. In: *The International Journal of Advanced Manufacturing Technology* 104.9 (2019), pp. 3647–3662.

[38] Dazhong Wu et al. “A comparative study on machine learning algorithms for smart manufacturing: tool wear prediction using random forests”. In: *Journal of Manufacturing Science and Engineering* 139.7 (2017).

MARIE CURIE ACTIONS

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