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Plastic parts and components analysis and origin for reuse optimisation

D5.8

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A Digital value chain Integration Traceability framework for process industries for Circularity and low Emissions by waste reduction and use of secondary raw materials

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Legal Disclaimer

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List of abbreviations and acronyms

Abbreviation	Meaning
CLSC Tool	Closed Loop Supply Chain Tool
WEEE	Waste of Electrical and Electronic Equipment
ML/DL	Machine Learning/Deep Learning
AI Algorithm	Artificial Intelligence Algorithm
SRMs	Secondary Raw Materials
PP	Polypropylene
ABS	Acrylonitrile Butadiene Styrene
HIPS	High-Impact Polystyrene (HIPS)
PA	Polyamide
PC-ABS	Polycarbonate- Acrylonitrile Butadiene Styrene
R&D	Research and Development
KPIs	Key Performance Indicators
CMM	Coordinate Measuring Machines
CSR	Customer-Specific Requirements
QC	Quality control
RGB	Red-Green-Blu
ERP	Enterprise Resource Planning
IoT	Internet Of Things
SPC	Statistical Process Control
DPP	Digital Product Passport
MES	Manufacturing Execution System
NIR	Near-Infrared
EOL	End-Of-Life
MRP	Material Requirements Planning
PET	Polyethylene Terephthalate
HDPE/LDPE	High-Density Polyethylene/ Low-Density Polyethylene

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Executive Summary

This document, "D5.8 Plastic Parts and Components Analysis and Origin for Reuse Optimisation," outlines a comprehensive framework developed by the DigInTraCE project for enhancing the efficiency of plastic recycling processes through the integration of advanced technologies and methodologies.

It begins with an introduction that sets the stage by explaining the primary purpose of the deliverable and identifying the intended audience. The DigInTraCE project focuses on enhancing plastic recycling by utilizing digital value chain integration and traceability. The ultimate goal is to promote circularity and achieve low emissions by reducing waste and maximizing the use of secondary raw materials (SRMs). Chapter 2 delves into the SIGIT use case, providing a thorough examination of the reuse optimization process. This chapter highlights how the methodologies proposed by the project are applied in a real-world scenario. It discusses the valorization process in detail, taking into account relevant regulations and legal considerations. This ensures that the recycling processes are not only efficient but also compliant with existing laws and environmentally sustainable. Chapter 3 offers insights into the target markets and finished products associated with the recycling of plastic materials. It identifies the specific types of polymer compounds and SRMs targeted for recycling, describing their characteristics and potential applications. This chapter also addresses the limitations where SRMs cannot be used, explaining the reasons behind these constraints. By doing so, it provides a clear understanding of the market dynamics and potential opportunities for recycled materials. In Chapter 4, the document outlines the advanced sensing and sorting techniques employed in the recycling process. These techniques are crucial for enhancing the accuracy and efficiency of material sorting, which is a critical step in the recycling chain. The chapter details the architecture of the vision-based sorting system and other innovative technologies used to optimize the sorting process. Chapter 5 focuses on the Closed-Loop Supply Chain (CLSC) Tool and its functionalities. It explains how this tool supports the supply chain by integrating IoT technologies for real-time data collection. The chapter covers the methodologies for planning, scheduling, and executing production orders, ensuring that the recycling processes are streamlined and efficient. The CLSC Tool plays a pivotal role in coordinating various aspects of the

recycling process, from collection to final processing. Chapter 6 provides an in-depth explanation of the AI algorithms developed for detecting and preventing anomalies in the recycling process. These machine learning algorithms are designed to enhance the reliability and efficiency of the recycling system by identifying potential issues early and implementing corrective actions. This chapter underscores the importance of AI in improving the overall performance and sustainability of recycling operations. The final chapter, Chapter 7, aims to integrate all the elements and technologies discussed in the previous chapters. It brings together the various components of the project, highlighting how they work in concert to optimize the plastic recycling process. The chapter also discusses mitigation strategies to address challenges, such as the exit of a key partner, and the steps taken to find new collaborators and adjust the project's focus and methodologies accordingly.

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1. Introduction

The DigInTraCE project focuses on improving plastic recycling by integrating digital value chain systems and enhancing traceability within process industries. The primary goal is to promote circularity and reduce emissions through effective waste management and the utilization of secondary raw materials (SRMs).

1.1. Purpose of the deliverable

This deliverable aims to enhance the efficiency of plastic recycling processes by focusing on three key areas:

1. **Detection of Pure Polymer Flakes**: Identifying unfiltered flakes in pure polymers to increase recycling efficiency. The target is an 8-9% increase in the total mass of polymers recycled, covering polypropylene (PP), acrylonitrile butadiene styrene (ABS), high-impact polystyrene (HIPS), polyamide (PA), and polycarbonate-ABS (PC-ABS).
2. **Identification of Reusable Compound Flakes**: Determining the main composition of flakes with reusable compounds to boost recycling by 5-7% of the total polymer weight.
3. **Preparation for Chemical Recycling**: Analyzing flakes with pure polymers and high molecular weight substances to prepare inputs for advanced recycling processes like pyrolysis and metanalysis, aiming to reduce waste mass incineration and hazardous substances in ashes.

Approach:

- **Initial Classification**: it will be conducted a thorough classification of flakes post-waste grinding and primary separation to determine their chemical composition. This process addresses the non-homogeneous nature of input waste, primarily sourced from Waste Electrical and Electronic Equipment (WEEE).
- **Chemical Analysis**: it will be identified unusable substances and pigments through chemical analysis to ensure only viable materials are processed further.
- **Machine Learning (ML) Techniques**: it will be designed ML models to monitor and optimize process parameters, including physical, thermal, and rheological data.

Roles and Contributions:

- **SIGIT**: Leverage its expertise in injection molding to provide requirements, input data, and support for the validation phase.
- **UVQ**: Develop data-driven techniques to optimize processes and recipes, and implement predictive analysis for injection molding control. Utilize ML and Control Theory methods (e.g., Regression Trees, Random Forests, Support Vector Machines, Neural Networks) to improve process efficiency and achieve key performance indicators (KPIs).
- **DGS**: Integrate the CLSC tool developed in T3.4 to streamline the process.

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Outcomes:

- Development and demonstration of optimized recycling processes and techniques.
- Reduction in wasted mass destined for incineration and a decrease in dangerous substances found in incineration ashes.
- Enhanced predictive capabilities and process control through advanced ML and Control Theory techniques.

Solutions will be demonstrated and validated in Work Package 6 (WP6) in the Italian Demo, ensuring practical applicability and effectiveness in real-world scenarios.

This deliverable represents a significant step towards sustainable plastic recycling, leveraging advanced technologies and interdisciplinary expertise to achieve measurable improvements in recycling efficiency and environmental impact.

1.2. Intended audience

The intended audience for this document is i) stakeholders involved in the DigInTraCE project, including researchers, engineers, and project partners focusing on the optimization of plastic parts and components reuse, as well as ii) entities interested in advanced recycling processes and circular economy practices. This is inferred from the technical nature of the content, the involvement of specific industrial and technological processes, and the emphasis on collaborative and interdisciplinary efforts within the project's scope.

1.3. Structure of the deliverable and its relation with other work packages/deliverables

The deliverable is structured into different chapters, listed in the table of contents and summarized in the Executive Summary. They serve the reader in deep-diving into the reusable process of plastic parts coming from WEEE, providing insights in enhanced predictive capabilities and process control through advanced AI Algorithms, sensing and sorting techniques.

The delivery of this document will provide data to WP6, where the solution will be demonstrated and quantified. Furthermore, it is related to WP3, where a detailed explanation of the novel sensing and sorting techniques is provided, along with an in-depth description of the Closed Loop Supply Chain Tool.

1.4. Main changes from previous version

This is the first version.

2. SIGIT - Use Case and The Reuse Optimization Process

SIGIT S.p.A. is a leading manufacturer specializing in the production of high-precision plastic and rubber components for various industrial applications, particularly in the automotive sector. With its headquarters in Italy, SIGIT operates multiple advanced manufacturing facilities equipped with cutting-edge technologies.

SIGIT's core competencies include:

1. **Injection Molding**: Utilizing state-of-the-art injection molding machines, SIGIT produces complex plastic components with high precision and consistency. The company's expertise in mold design and process optimization ensures superior product quality and efficiency.
2. **Rubber Molding**: SIGIT specializes in the production of molded rubber parts, employing both compression and injection molding techniques. These components are engineered to meet specific performance requirements, including durability, elasticity, and resistance to various environmental factors.
3. **Assembly**: Beyond molding and extrusion, SIGIT offers comprehensive assembly services, integrating molded components with other materials and parts to deliver complete, ready-to-use products.
4. **Tooling and Mold Making**: SIGIT's in-house tooling department designs and manufactures high-precision molds and dies, enabling rapid prototyping and production scalability. This capability allows for tight control over the quality and timelines of new product developments.
5. **Quality Control**: Employing rigorous quality control processes, SIGIT ensures that all products meet stringent industry standards. Advanced inspection and testing equipment, including CMM machines and various non-destructive testing methods, are used to verify the dimensions and properties of finished components.
6. **Research and Development**: SIGIT is committed to continuous improvement and innovation. The R&D team focuses on material science, process engineering, and product design to develop new solutions and enhance existing products. Collaboration with academic institutions and industry partners supports this ongoing effort.
7. **Sustainability**: The company implements environmentally friendly practices across its operations, from material selection to waste management, aligning with global sustainability standards.

SIGIT S.p.A. is recognized for its technical excellence and ability to deliver high-quality, reliable components tailored to the specific needs of its clients. Its advanced manufacturing capabilities and commitment to innovation position SIGIT as a key player in the global industrial landscape.

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2.1. Reuse Optimization Process

In recent years, the proliferation of electronic devices has led to a surge in electronic waste (e-waste), posing significant environmental challenges globally. Among the various components of e-waste, plastic materials present a particularly complex recycling scenario due to their diverse compositions and the presence of contaminants. To address this issue, innovative approaches to plastic recycling are essential, focusing on the recovery and reuse of mixed polymeric materials obtained from Waste of Electric and Electronics Equipment (WEEE).

The Italian Demo case represents a comprehensive effort to tackle the complexities of plastic recycling within the context of e-waste management. The process begins with the collection and sorting of WEEE, encompassing a wide range of electronic and electrical devices, from refrigerators and air conditioners to washing machines and photovoltaic panels. These devices contain a plethora of plastic components, each with its own unique properties and composition.
Once collected, the WEEE undergoes a multi-stage recycling process aimed at recovering valuable materials and minimizing environmental impact. The initial stages involve mechanical sorting, where devices are dismantled, and components are separated based on material type. Metals, organic substances, electronic boards, and plastic and rubber parts are segregated into distinct streams, each destined for further processing.

One significant challenge within the recycling process arises from the handling of what is termed "heavy plastics." This intermediate fraction consists of flakes with an average density of 1.1 Kg/dm^3, rendering them unsuitable for traditional mechanical separation methods. The presence of impurities, such as flame retardants (e.g., brominated compounds), further complicates the recycling process. However, despite these challenges, the heavy plastics fraction contains valuable polymers and compounds that warrant recovery and reuse.

To address the complexities of heavy plastics recycling, the Italian Demo case leverages innovative technologies and methodologies. Advanced sorting techniques, including spectroscopic analysis and molecular identification, enable the precise characterization of plastic flakes, facilitating targeted recovery efforts. Additionally, chemical analysis is employed to identify and mitigate the presence of contaminants, ensuring the quality and purity of recycled materials.
The industrial recycling plant involved in the Demo case operates at a significant scale, processing up to 30,000 tons per year of input. This substantial throughput underscores the importance of efficient and effective recycling methods to manage the growing volumes of e-waste generated globally. The heavy plastics fraction, comprising 18 to 20 percent of the total input, represents a substantial portion of the material processed, highlighting its significance within the recycling operation.

Ultimately, the Italian Demo case exemplifies the transition toward a circular economy, where resources are used, reused, and recycled in a closed-loop system. By maximizing the recovery and reuse of plastic materials from WEEE, the project contributes to the reduction of waste, conserves natural resources, and mitigates environmental pollution. Moreover, by integrating innovative technologies and collaborative approaches, the project sets a precedent for sustainable practices in plastic recycling that can be replicated and scaled globally.

2.2. General Description of The Proposed Valorization Process

The treatment of Waste Electrical and Electronic Equipment (WEEE) is a critical component of modern waste management, driven by stringent regulations and the need for sustainable practices. In Italy, the process is managed by companies authorized to recover and recycle waste, adhering to a complex legal framework that governs the entire value chain from waste collection to the availability of secondary materials.
This section aims to provide an in-depth look at the pure recycling macro phases of WEEE treatment, depicted in Figure 1, highlighting the key steps and methodologies involved.

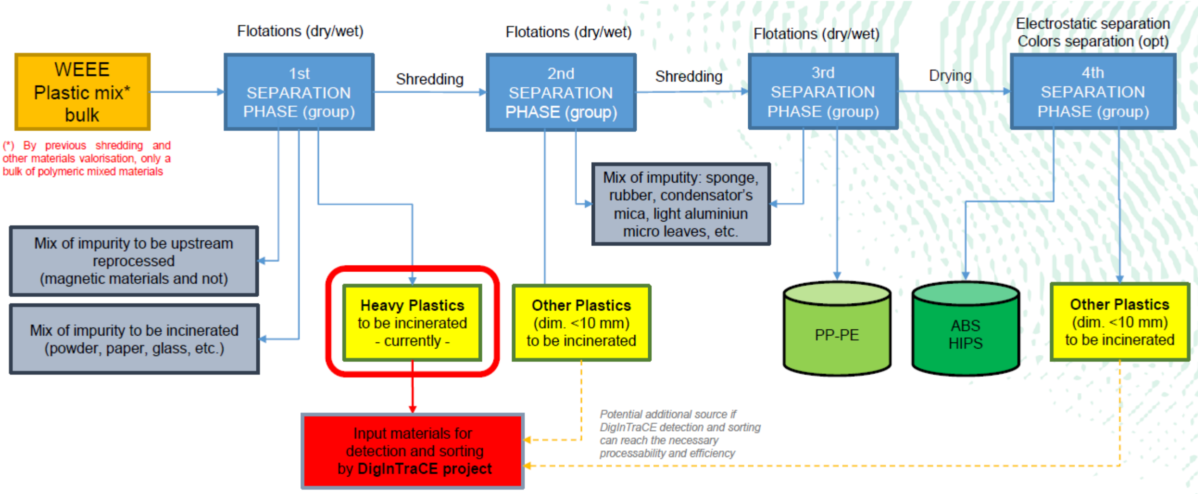

Figure 1: Macro schema of the WEEE valorization process

The seven macro phases are:

1. **Initial Shredding and Separation**

The recycling process begins with the shredding of collected WEEE. This step is crucial as it breaks down large electronic devices into smaller, more manageable pieces. Following shredding, the materials pass through a series of mechanical and magnetic screens designed to remove foreign materials. Iron, powders, magnetic substances, glass, and paper are separated during this phase. This multi-step process ensures that only the desired thermoplastic mix progresses to the next stage, while contaminants are systematically removed.

2. Flotation for Metal Removal

After the initial separation, the plastic fragments undergo a flotation process. Flotation is an effective method for removing metals and other residual materials. During this phase, the materials are immersed in water, where differences in density cause metals and other impurities to sink or float, facilitating their removal. While flotation significantly reduces the presence of unwanted materials, it is not entirely foolproof, and some contaminants may remain.

3. Advanced Cleaning and Removal of Non-Plastics

The subsequent cleaning phase involves the removal of non-plastic fragments such as wood, sponge, and rubber. This is achieved through a combination of dry and wet flotation techniques, which further purify the plastic waste. Plastics containing flame retardants or those with a density greater than 1.1 Kg/dm^3 are also identified and separated during this stage. These steps are vital to ensure that the remaining plastic material is as homogeneous and contaminant-free as possible.

4. Homogenization and Grinding

To enhance the uniformity and facilitate further separation, the plastic materials are ground into smaller particles, typically around 10-12 mm in size. Grinding the plastic into finer particles makes it easier to handle and increases the efficiency of subsequent separation processes. This homogenization is a critical step in ensuring that plastic waste can be effectively sorted and recycled.

5. Density-Based Separation

The next phase of the process involves separation by density. Different types of plastics have varying densities, which can be exploited to segregate them. Polypropylene (PP) and polyethylene (PE) are lighter and tend to float, whereas high-impact polystyrene (HIPS) and acrylonitrile butadiene styrene (ABS) are denser and sink. This density-based separation is instrumental in isolating specific types of plastics, which can then be processed further.

6. Dry Line Separation

In the dry line separation phase, polystyrene and ABS are separated from rubber residues, wood, and other small impurities. Electrostatic separators play a crucial role here, leveraging the differences in electrical properties to distinguish between materials. Once separated, the ABS and HIPS undergo further refinement in a flotation tank, where HIPS with additives is divided from HIPS without additives. This meticulous separation process ensures that each type of plastic is purified to the highest possible degree.

7. Color Selection

As a final step in the sorting process, color selection may be performed, particularly for "white HIPS" derived from Class W1 recycling (e.g., refrigerators and freezers).

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This step is essential for applications where color uniformity is critical, enhancing the aesthetic and functional quality of recycled plastic.
Despite the comprehensive nature of these separation processes, not all fractions can be perfectly sorted. Some materials fall outside the density range of the treatment plant's capabilities, or they may not be adequately separated due to the high throughput requirements, which prevent fine separation of every single flake. Consequently, these fractions, which still contain valuable polymers, are often designated for waste-to-energy processes, where they are incinerated to generate energy.

The project DigInTraCE aims to address these challenges by optimizing the detection and sorting phase of the recycling process. By enhancing the ability to identify and separate usable polymers from mixed fractions, the project seeks to increase the overall efficiency and effectiveness of plastic recycling. The input materials for DigInTraCE are derived from the fractions that current processes struggle to separate efficiently. These materials, which would otherwise be incinerated, provide a valuable resource for developing improved recycling technologies.

2.3. Regulatory and Environmental Considerations

The stringent Italian regulatory environment plays a crucial role in shaping the recycling process. Regulations ensure that companies adhere to high standards of environmental protection and resource recovery, but they also add layers of complexity to the recycling chain. From the initial collection of WEEE to the final availability of secondary materials, every step is governed by detailed legal requirements designed to minimize environmental impact and promote sustainability.
Looking ahead, the future of WEEE recycling lies in continuous innovation and improvement of existing processes. Projects like DigInTraCE represent a significant step forward in this regard, leveraging advanced technologies such as machine learning and data-driven optimization to enhance sorting and detection capabilities. By refining these processes, it is possible to increase the recovery rates of valuable polymers, reduce the volume of waste destined for incineration, and minimize the environmental footprint of electronic waste.

3. Target Markets and Finished Products

The primary goal of the recycling process outlined is the production of Secondary Raw Materials (SRMs) from high percentages of materials recovered from Waste Electrical and Electronic Equipment (WEEE). SRMs are essentially formulated from pure polymers and polymeric compounds, aiming to create new injection-molded plastic components. The study focuses on improving the types of polymeric compounds processed and enhancing the overall efficiency of the recycling process. This involves a detailed examination of field and reprocessing technologies, market targets, and compliance with complex regulations and technical specifications.

3.1. Polymer Compounds and SRMs

The recycling process transforms recovered materials into polymer compounds, which are then used to produce SRMs. These SRMs are crucial for creating new plastic components via injection molding. However, it is important to note that pure polymers are rarely used in their unblended form due to the stringent requirements set by customers. Instead, polymers are often compounded with various additives to meet specific performance and compliance standards.

Pure polymers obtained from the recycling process are typically sold to external compounding companies that specialize in creating tailored blends. These companies are equipped with the expertise and technology to modify the properties of the polymers to suit different applications. However, this aspect is not within the scope of the Italian Demo Case of DigInTraCE, which focuses primarily on developing SRMs for direct use in new product manufacturing.

3.1.1. Injection Molding

Injection molding is a widely used manufacturing process for producing plastic components. It involves injecting molten polymer into a mold cavity, where it cools and solidifies into the desired shape. The use of SRMs in injection molding requires a deep understanding of the material properties and the specific requirements of the end products. Formulating SRMs that can perform reliably under various conditions and meet customer specifications is a significant challenge.

The efficiency of the injection molding process can be significantly impacted by the quality of the SRMs. Impurities or inconsistencies in the material can lead to defects in the final products, increasing waste and production costs. Therefore, continuous improvements in the recycling process, including better sorting, cleaning, and compounding techniques, are essential to produce high-quality SRMs.

3.2. Target Markets

The SRMs produced from recycled WEEE materials have diverse applications across several industries. Key target markets include:

- **Small and Large Domestic Appliance Equipment**

The domestic appliance market is one of the largest consumers of plastic components. SRMs can be used to manufacture various parts for appliances such as refrigerators, washing machines, dishwashers, and air conditioners. These applications require materials that can withstand mechanical stress, temperature variations, and chemical exposure.

- **Transportation**

The transportation sector, including automotive, light and heavy commercial vehicles, agriculture, and construction tractors, is another significant market for SRMs. Plastics in this sector are used for a wide range of applications, from interior components to under-the-hood parts. Materials used in transportation must meet stringent safety, durability, and performance standards, making the development of suitable SRMs a complex task.

- **General Purposes**

Beyond specific industries, SRMs have general-purpose applications in various consumer goods, electronics, and packaging. The versatility of SRMs allows them to be used in multiple products, provided they meet the required specifications for each application.

3.2.1. Regulatory and Technical Challenges

The recycling and use of SRMs in new products are governed by a complex web of regulations and technical specifications. These requirements vary significantly depending on the target market and the specific application of the materials.

3.2.1.1. Compliance and Homologation

Compliance with customer-specific requirements (CSR) is a critical aspect of using SRMs. Each customer or industry has unique standards and regulations that materials must meet to be approved for use. For example, in the automotive industry, a new material must be homologated by the product supplier and meet 30-40 different norms before it can be used in a vehicle.

This homologation process is expensive and time-consuming, requiring extensive testing and validation to ensure that the material performs as expected under all conditions. For Sigit, the ability to create ad hoc formulations that meet these stringent requirements is essential. This requires a high level of expertise in both materials science and regulatory compliance.

3.2.1.2. Material Properties and Specifications

The technical specifications of each new compound used to produce SRMs are detailed and demanding. These specifications cover a wide range of properties, including mechanical strength, thermal stability, chemical resistance, and environmental impact. Meeting these specifications requires precise control over the recycling and compounding processes.

For instance, the presence of flame retardants, plasticizers, or other additives in the recycled material can significantly affect its properties. Therefore, accurate detection and removal of impurities during the recycling process are crucial. Advanced technologies, such as machine learning and data-driven optimization, can help monitor and control these parameters to ensure consistent quality.

3.2.2. Continuous improvement

Continuous improvement in the recycling process is vital to enhance the efficiency and quality of SRMs. The following areas are critical for achieving these improvements:

Advanced detection and sorting technologies are essential for improving the purity of recycled materials. Techniques such as near-infrared spectroscopy, X-ray fluorescence, and electrostatic separation can help identify and remove contaminants more effectively. Machine learning algorithms can also be used to optimize these processes, reducing errors and increasing throughput.

Effective cleaning and purification steps are necessary to remove non-plastic materials and additives from the recycled polymers. This includes both dry and wet flotation techniques, which can separate different types of plastics based on their density and other physical properties. Improved cleaning processes can lead to higher-quality SRMs, which are more suitable for demanding applications.

The **compounding process** involves blending recycled polymers with additives to achieve the desired properties. This step is critical for tailoring the SRMs to specific applications and ensuring they meet all regulatory and performance requirements. Advanced compounding techniques, including the use of twin-screw extruders and reactive extrusion, can enhance the properties of the recycled materials and create high-performance blends.

Furthermore, implementing robust process monitoring and control systems is essential for maintaining the quality and consistency of SRMs. This includes real-time monitoring of key parameters, such as temperature, pressure, and material flow, as well as advanced data analytics to predict and correct any deviations. Machine learning and artificial intelligence can play a significant role in optimizing these processes, leading to more efficient and reliable recycling operations.

3.2.2.1. Advanced Recycling Technologies

Emerging recycling technologies, such as chemical recycling and pyrolysis, offer new ways to recover valuable materials from complex waste streams. These technologies can break down plastics into their basic chemical building blocks, which can then be reprocessed into high-quality polymers. While still in the early stages of development, these advanced recycling methods hold great promise for improving the efficiency and sustainability of the recycling process.

3.2.2.2. Collaboration and Partnerships

Collaboration between different stakeholders, including waste management companies, recyclers, manufacturers, and regulators, is essential for advancing the recycling process. By working together, these stakeholders can share knowledge, develop new technologies, and create more effective recycling systems. Partnerships with research institutions and technology providers can also help drive innovation and improve the overall efficiency of the recycling process.

3.2.2.3. Consumer Awareness and Engagement

Increasing consumer awareness and engagement is crucial for the success of recycling programs. Educating consumers about the importance of recycling and how to properly dispose of electronic waste can help increase the volume and quality of materials available for recycling. Additionally, encouraging consumers to purchase products made from recycled materials can create a stronger market for SRMs, driving further investment and innovation in the recycling industry.

3.3. Which markets cannot be reached and why?

The use of Secondary Raw Materials (SRMs) sourced from the recovery of Waste Electrical and Electronic Equipment (WEEE) offers significant environmental benefits and contributes to the circular economy. However, SRMs derived from WEEE have certain technical limitations that restrict their applicability in some fields. These limitations are primarily due to the heterogeneous nature of the feedstock and the presence of contaminants that are difficult to eliminate entirely. This text will explore the specific challenges associated with using SRMs from WEEE in packaging, medical applications, aesthetically sensitive products, transparent materials, and food contact items.

3.3.1. Packaging

One of the primary challenges of using SRMs from WEEE in packaging applications is the diverse composition of the recovered polymers. Packaging often requires specific types of polymers that possess particular properties such as flexibility, strength, and barrier resistance. However, SRMs from WEEE are typically a mix of various polymers, including polyethylene (PE), polypropylene (PP), polystyrene (PS), and acrylonitrile butadiene styrene (ABS). This mixed composition makes it difficult to achieve the uniform properties required for packaging materials. Additionally, transparency is a critical requirement for many packaging applications, especially for products where consumers need to see the contents, such as food and beverage packaging. Achieving transparency with SRMs from WEEE is challenging due to the presence of various pigments and additives in the original electronic products. These contaminants can create opacity or discoloration, making it difficult to produce clear films and foams from the recycled materials. Moreover, the production of films and foams from SRMs is particularly challenging due to the presence of contaminants and the mixed nature of the feedstock. Films and foams require precise control over polymer properties such as melt flow index and molecular weight distribution. The heterogeneity of SRMs makes it difficult to achieve the consistency needed for these applications, leading to defects and variations in the final products.

3.3.2. Medical Applications

The medical industry has stringent requirements regarding the purity and safety of materials used in medical devices and packaging. Any contaminants present in the materials can pose significant health risks to patients. As a result, SRMs from WEEE are generally unsuitable for medical applications due to the difficulty of ensuring complete removal of contaminants. The diverse nature of the feedstock means that even trace amounts of unwanted substances could be present, which disqualifies these materials from use in medical products.

Medical applications are subject to rigorous regulatory standards that demand absolute purity and biocompatibility. Achieving these standards with SRMs is nearly impossible due to the potential for contamination from the original electronic waste. Consequently, the use of SRMs in the medical field is highly restricted, and alternative sources of pure, virgin polymers are typically required.

3.3.3. Aesthetically Sensitive Products

Aesthetically sensitive products, such as consumer electronics, automotive interiors, and high-end appliances, often require materials with specific colors and finishes. The presence of pigments and masterbatches in SRMs from WEEE can create inconsistencies in color and appearance. These pigments, originally added to the electronic products for specific purposes, remain in the recycled materials and can lead to undesirable aesthetic outcomes. Maintaining uniformity in color and finish is crucial for aesthetically sensitive products. The variability in the composition of SRMs can result in color inconsistencies and surface defects, making these materials less suitable for applications where appearance is a critical factor. High-quality control measures are necessary to ensure that recycled materials meet the stringent aesthetic requirements, which can be challenging and cost-prohibitive with SRMs from WEEE.

3.3.4. Transparent Materials

The use of SRMs from WEEE for producing transparent materials faces significant hurdles due to the presence of embedded pigments. These pigments, which were part of the original electronic products, cannot be completely removed during the recycling process. As a result, achieving the clarity and transparency required for certain applications, such as optical components or clear packaging, is difficult. Transparent materials often require high optical quality and performance, with minimal haze and excellent light transmission.

The presence of even small amounts of pigments or other impurities can significantly degrade these properties. Therefore, SRMs from WEEE are generally unsuitable for applications where optical clarity is essential, and virgin polymers or more thoroughly processed recycled materials are preferred.

3.3.5. Food Contact Applications

Food contact applications, including packaging and utensils, have strict regulations regarding the presence of contaminants. These regulations are designed to ensure the safety and hygiene of food products. SRMs from WEEE are challenging to use in food contact applications due to the difficulty of completely removing contaminants that might pose health risks. The mixed nature of the feedstock and the presence of substances from the original electronic products create significant barriers to compliance with food safety standards.

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Furthermore, legal and normative constraints in many regions prohibit the use of recycled materials with unknown or potentially hazardous contaminants in food contact applications. Ensuring that SRMs meet these stringent requirements involves extensive testing and certification processes, which can be impractical given the variability and potential contamination of WEEE-derived materials. As a result, SRMs from WEEE are typically not used for food contact items, and alternative sources of pure, compliant materials are sought.

The recycling process for producing Secondary Raw Materials (SRMs) from WEEE is a complex but essential component of sustainable waste management. By focusing on advanced detection, sorting, cleaning, and compounding techniques, the recycling industry can produce high-quality SRMs that meet stringent regulatory and performance requirements. Targeting key markets, such as domestic appliances and transportation, ensures that these materials are used effectively and contribute to a circular economy.
Continuous improvement and innovation in recycling technologies, coupled with strong collaboration and consumer engagement, are vital for the future success of SRMs. As the industry evolves, the ability to produce high-quality recycled materials will play a crucial role in reducing environmental impact and creating more sustainable products. The DigInTraCE project represents a significant step forward in this effort, leveraging advanced technologies and collaborative efforts to enhance the recycling process and the quality of SRMs produced.

4. Sensing and sorting

A sorting system for the valorisation of the plastics secondary stream will be built within the DigInTraCE project, namely in T3.2 and will be detailed described in Deliverable 3.3. This development aims to separate various plastic granules according to their composition. However, because of the shift in pilot owners (already described in D3.7, Chapter 5 'SIGIT - Use case and challenges faced'), the plastic sorter's advancement has been postponed until the new pilot owners formally join the consortium.
Though the new pilot requirements and specifications are mostly unchanged from the old one, the plastic sorter partners were able to move forward with some rudimentary developments to meet the T3.2 time schedule as close to the deadline as possible.
More specifically, IRIS is in charge of the material characterisation of the plastic sample, and deliverable 3.1 includes a thorough description of the work in progress. The primary goal of the analysis is to identify the specific components present in each plastic flake. This detailed characterization involves advanced techniques which help to determine the polymer type, presence of additives, and possible contaminants.
By precisely identifying the composition of each flake, IRIS aims to:

1. Enhance the understanding of the material properties.
2. Identify potential challenges in the recycling process.
3. Provide data to improve sorting and processing techniques.

Following the detailed material analysis, a machine learning (ML) algorithm designed to optimize the recycling process has to be applied. At this stage, the algorithm aims to Improve the accuracy of sorting techniques by predicting the polymer type and quality based on the physical and chemical properties of the flakes.
The ML model has to be trained using the data obtained from the initial analysis and continuously refined through iterative learning. This approach ensures that the model could adapt to new data and improve its predictions over time.
To further support the development and validation of the ML algorithm, SIGIT, has to provide technical datasheets for several of its finished products. These datasheets should include detailed information about the nominal bill of materials (BOM) used in the production of these products, specifying the virgin plastics involved.
The inclusion of this information allows for:

1. A direct comparison between the recycled materials analyzed and the virgin materials specified in the BOM.
2. Identification of any discrepancies between the properties of recycled and virgin plastics, enabling targeted improvements in the recycling process
3. Validation of the ML algorithm's predictions by comparing the characteristics of recycled plastic against the specifications of the virgin material used in finished products.

Regarding the sorting design leaded by ICCS, it will have three primary levels. To begin with, a pretreatment unit will be employed ensuring a uniform and even distribution of samples down the conveyor belt. Subsequently, the sorting system will incorporate the output of the T3.1 sensing system supplied by IRIS, feeding the convolutional networks of ICCS to achieve high levels of accuracy in material classification and image processing. In the end, an air nozzle system will be developed, aiming the final separation stage, which will be carried out by using the output of the ML/DL models.

4.1. High-Level Overview of the vision-based architecture of Sorting system

ICCS has developed a vision-based architecture specifically designed for the automated sorting of plastic waste. This system utilizes cutting-edge artificial intelligence (AI) and multi-sensor technologies to efficiently identify, classify, and sort various types of plastic materials on a conveyor belt, significantly enhancing the recycling process's accuracy and efficiency.

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To gain a comprehensive insight into the functionalities and key components of the vision-based architecture developed by ICCS for automated plastic waste sorting, the following Table 1 outlines the core modules and their roles in the sorting process:

Table 1: Core Components and Workflow

Component	Description
Multi-Sensor Integration	The system integrates RGB (Red, Green, Blue) and multi-spectral cameras (HSI) to capture comprehensive imagery across different wavelengths. This multi-sensor setup provides detailed visual data that is essential for distinguishing between various plastics based on their unique spectral characteristics.
Detection and Segmentation	The sorting process begins with the detection module, which is AI-powered and responsible for recognizing and segmenting plastic objects on the conveyor belt. This module uses deep neural networks to analyze frames from the RGB camera in real-time, generating binary masks that outline each plastic object's shape and position. Each object is assigned a unique digital ID to track it accurately through the sorting stages.
Synchronization and Coordination	The synchronization module ensures seamless operation by coordinating the timing and actions of all system components. It synchronizes the cameras to capture optimal images of the plastic objects as they move along the conveyor and triggers the robotic arm at the correct moment for picking and sorting. The module considers factors like conveyor speed, camera positions, and the robotic arm's location to maintain precise control.
Multi-Modal Classification	The classification module processes data from various sensors to determine the type of plastic material. It uses an auto-encoder-based AI framework with parallel encoders to handle inputs from different imaging modalities, including RGB, visible light, and near-infrared (NIR). By combining these inputs, the system accurately classifies the plastic type, such as PET, HDPE, and LDPE.
Robotic Sorting	After classification, detailed information about the plastic type and its position is relayed to the robotic subsystem. The robotic arms are guided to pick and sort the plastics accordingly, ensuring each material is directed to the appropriate recycling stream. This automated process enhances the purity and quality of the sorted plastic, preparing it for further recycling processes.

The key innovations and advantages of the ICCS Vision-Based Agnostic System for plastic waste sorting are described in the following table:

Table 2: Key Innovations and Advantages of the ICCS Vision-Based Agnostic System

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Feature	Description
Agnostic Sorting Capability	One of the system's standout features is its agnostic sorting capability. It is designed to handle various plastic types without the need for specific reconfigurations, making it versatile and suitable for a wide range of recycling applications.
Enhanced Accuracy and Efficiency	Leveraging advanced AI for precise detection and classification, the system significantly reduces the risk of misclassification and contamination. Multi-spectral imaging aids in distinguishing between plastics that may appear similar under standard lighting conditions.
Real-Time Processing	The system operates in real-time, which is crucial for maintaining high throughput and efficiency in industrial plastic recycling operations. It keeps pace with the continuous flow of materials on the conveyor belt, ensuring timely and efficient sorting.
Reduction of Manual Labor	By automating the sorting process, the system reduces dependence on manual sorting. This automation minimizes human error and increases overall safety and productivity in recycling facilities.

The ICCS vision-based system represents a significant technological advancement in the field of automated plastic waste sorting. By integrating sophisticated multi-sensor technology with state-of-the-art AI, this system supports the effective and sustainable management of plastic waste streams. It contributes to the broader goals of a circular economy and helps reduce the environmental impact of plastic waste.

Both the sensing and sorting techniques will provide insights and data into the DPP, making the whole process traceable and supporting the CLSC Tool to identify and schedule the use of the reusable material into the production system.

5. CLSC Tool – planning, scheduling and MES

What is the CLSC tool role? The idea of the project is to utilize the Scheduling and MES modules to optimize the supply chain by the means of AI algorithms, which will support the manufacturing system predicting production drifts and helping to identify cause-effects events related to defects.
Through the SIGIT's IoT Layer a wide range of data will be collected initially, from machinery conditions and parameters (temperature, pressure, humidity, level of plastic into the nozzles…) to production information such as pieces manufactured, pieces discarded, manufacturing times. Those data will be available not only to the Manufacturing Execution System but also to the AI algorithm, which will implement a classification algorithm able to predict/detect, on the basis of the run-time reads of the molding machine data, the production of a defective piece. Such algorithm will base on a mathematical model constructed offline, on the basis of historical training datasets.

The AI algorithms, in case of anomalies predicted analyzing data real-time, will send events or warning messages to the Scheduling Module, which will adopt the on-going production plan introducing for instance maintenance events to the plan. Recognizing production drifts or even better anticipating them, will generate a positive effect reducing waste and energy consumption. Step by step, through a continuous improvement mindset, the production model will become increasingly precise and reliable, allowing for a more accurate identification of the cause-effect relationships behind the defective parts.

In the following paragraphs it will be described the process related to the CLSC Tool and a dedicated chapter is left to the in-depth explanation of the AI algorithms logics.

5.1. IoT layer and data collection

An extremely relevant point in this project is the IoT layer and the Open Plast interface. Open Plast is an Italian platform developed by Polimatica S.r.l. for Industry 4.0, proposed as a ready-to-use solution dedicated to the world of plastics and rubber, particularly focusing on the injection molding of technopolymers and rubber, as well as the extrusion of sheets or technical components.

The platform collects and standardizes production process data generated by machines, which often use different standards and protocols such as EUROMAP 63, EUROMAP 77, OPC-UA, MODBUS/RTU, MODBUS/TCP, and SIEMENS S7. The system operates on a local server located within the factory and utilizes cloud technology for additional data processing and storage.

The injection molding machineries are capable of providing a vast array of parameters, some of them have never been used by SIGIT, therefore the analysis of the interface between the CLSC Tool (MES module) will be necessary. For security reasons related to the presence of operators into the production floor, only the following data shown on Table 3 can be adjusted automatically also by the MES directly to the machinery.

Table 3: Editable production parameters

Type	Description
Active Cavities	Cavities currently active
Blocked Cavities	Cavities currently blocked
Declared Cause	Declared cause
Rejected Parts	Defective parts
Declared Reject Cause	Declared reject cause
Operator On Duty	Operator on duty
Lot Throughput	Lot throughput
Lot Quality Rate	Lot quality rate
Good Parts Yield (Lot)	Good parts yield (lot)
Remaining Lot Time	Remaining lot time
Remaining Lot Quantity	Remaining lot quantity

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Total Cavities	Total cavities
Order Number in Progress	Order number in progress
Article in Progress	Article in progress
Customer Odp in Progress	Customer Odp in progress
Material Code in Progress	Material code in progress
Material Lot Code in Progress	Material lot code in progress
Remaining Lot Processing Time Below Threshold	Remaining lot processing time below defined threshold
Lot Downtime Exceeds Threshold	Lot downtime exceeds defined threshold
Raw Material Depletion	Raw material depletion
Production Start Approval Request (Remaining Setup Time Below Threshold)	Request for production start approval (remaining setup time below defined threshold)

5.2. Scheduling and execution of production orders

The recycled raw material is introduced into the plant during warehouse operations. Upon delivery, an operator records its receipt in the ERP system using the bill of lading. Subsequently, this information is integrated into the plant's inventory, allowing it to be utilized in production orders according to demand. The operator has access to the production plan, while the Scheduling Module manages the production floor by specifying which production orders require the specific material and when, based on an optimized sequence that typically considers molding constraints and parameters.
The pieces of information listed in Table 4 are generally extracted from the ERP and they serve the Scheduling Module as main data.

Table 4: Manufacturing data exchanged with the ERP

Data Family	Data Details	Notes	Frequency
Resource Master Data	▪ Work center ▪ Attribute classification	Work centers together with information related to shifts and company calendars will be imported into the CLSC Tool. Attributes for work centers will not be used at the beginning.	▪ Daily bulk ▪ On Demand ▪ Incremental mode can be enabled
Operator Master Data	▪ Operator ID	Operator master data will be extracted to enable their association with machines in the MES.	▪ Daily bulk ▪ On Demand ▪ Incremental mode can be enabled
Material Master Data	▪ Unit of measure ▪ Materials	Material master data for the specific material types to be managed will be extracted. Other surrounding master	▪ Daily bulk ▪ On Demand

	▪ Attribute classification ▪ Revision levels ▪ Production versions	data, such as units of measure, attributes, and revision levels, will also be extracted. The following attributes must be extracted: • Article color • Color range ("weight" for each color) • Preferred mold • Active cavities (used only if not explicitly managed in the cycle)	
Molds	▪ Equipment master data ▪ Extraordinary maintenance orders	Equipment master data is extracted and also extraordinary maintenance orders related to molds	▪ Daily bulk ▪ On Demand ▪ Extraordinary maintenance orders
Routings	▪ Routing per item ▪ Attribute classification	Valid routings for all finished, semi-finished, and assembled products will be extracted. The routing includes the preferred work center with machine and operator production times and machine and operator setup times. The base quantity also includes the number of active cavities. The following attributes must be extracted: ▪ Associated mold (if not unique) ▪ Associated articles (additional information, currently unavailable ▪ Possible alternative presses	▪ Daily differential ▪ On Demand ▪ Potential weekly or monthly mass reconciliation
Bill of Materials	▪ Bill of materials per item	Valid BOMs for each finished, semi-finished molding, and assembled product will be extracted. Both the committed quantity and the base quantity, which should indicate the cavity reference consumption, are present.	▪ Daily differential ▪ On Demand ▪ Potential weekly or monthly mass reconciliation

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Planned Orders	▪ Planned production orders	Extraction of planned production orders with quantity and requested date determined by the MRP	▪ Daily bulk ▪ On Demand
Production Orders	▪ Production orders	Extraction of all production orders not yet closed in the ERP. Each production order carries its associated BOM and routing, with information on partially or fully issued components, and quantities of phases already confirmed and phases already closed.	▪ High Frequency incremental *New orders, status changes, and quantity changes must be extracted with high frequency to keep the CLSC Tool always aligned with the ERP.*
Sales	▪ Sales orders ▪ Delivery plan	Demand data is useful for Scheduling to highlight which production orders were generated for which requests and the delivery deadlines. It is important that the quantity data is always net of already shipped quantities.	▪ Daily or multi-daily bulk
Purchases	▪ Purchase orders ▪ Delivery plan	Purchase plans data is important to allow the scheduler to simulate the stock trend of critical materials. The quantity data must always be net of already delivered amounts (confirmed receipt).	▪ Daily or multi-daily bulk
Stock Availability	▪ Stock	Extraction of the inventory	▪ Daily or multi-daily bulk

As written above, the primary input for the Scheduler will be the order proposals calculated by the MRP and the already created production orders with their status. Based on the parameters and rules set in the system the Scheduler will calculate an optimal production sequence for the Molding department.
In the Scheduler, it will be possible to:

- Modify the quantities proposed by the MRP
- Combine multiple proposals into a single order
- Modify the production start date proposed by the MRP

- Change the association to the work center by choosing from the available alternatives
- Assign a different production version from the preferred one set in the ERP

Once the sequence is confirmed and released, data will be sent back to the ERP, which will result in:

- For order proposals: the conversion into production orders, the recording of a scheduled start and end production date, and the association to a work center
- For already converted orders: the definition of the start and end production date and the association to a work center

Based on the sequence set by the Scheduler, the release of production orders will be carried out daily in ERP, which includes checking the availability of raw materials or semi-finished products in the warehouse and, if positive, assigning the corresponding batch in the warehouse.

Through a user-friendly interface, the operator will be able to see the whole production orders and their percentage of completion as shown in Figure 2.

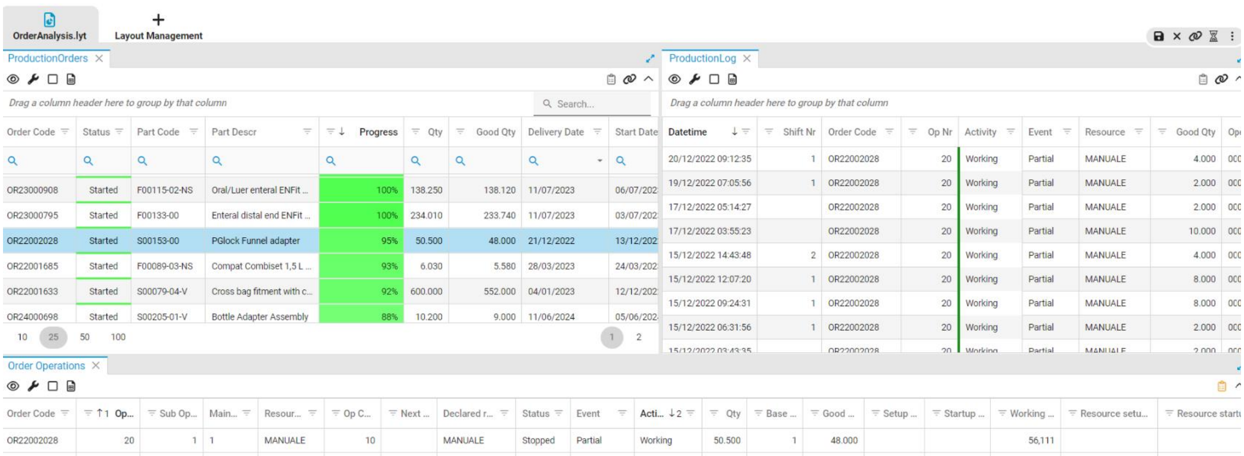

Figure 2: Production order analysis

A Gantt representation will be available too, where it will be possible to analyze the several production orders scheduled for individual machines Figure 3.

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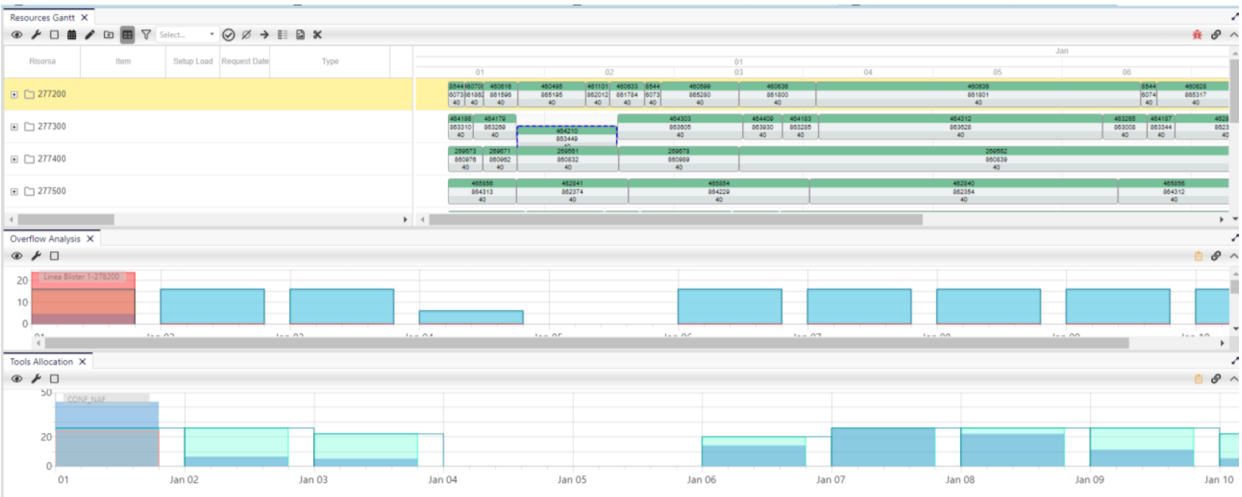

Figure 3: Production Gantt

The production schedule can be dynamically adjusted through the integration of AI algorithms. These algorithms generate events via Microsoft LogicApp technology, prompting maintenance orders based on detected anomalies, such as deviations in temperature or pressure. The operator is then presented with the option to either accept or reject these maintenance recommendations.
Once the daily production plan has been confirmed, production can become executable and therefore, at this point, is better to start talking about MES.

The work centers involved are presses, assembly benches, and other production machinery. The system allows associating:

- One or more operators for each Work Center
- One or more Work Centers for each operator

The main phases that will be involved in the MES system are:

1. Setup phase
2. Startup phase
3. Processing phase
4. Quality control and scrap declaration phase

The setup phase consists of the preparation and loading of the machine by a technician. The startup phase, which follows the setup phase in the case of a new order, consists of an initial manufacturing phase of items. They require quality-control check because in the startup phase defective parts may be produced until the machine reaches full operational efficiency. The production phase always begins with the declaration of the Start Processing Time by the direct operator, following the startup phase. The system will calculate the total number of pieces produced for each production order, for each item. This calculation will take into account the number of operational cavities and the number of figures in production on each Work Center (parallel orders) and the actual production recorded in real-time by the MES on the Work Centers. The determination of the number of cavities will be recorded in the routings master data. If the number of cavities is not in the cycle master data, it is assumed to be equal to 1.

The quality control activity is divided into the following steps:

- **Operator Self-Inspection on the Line**: Every X hours, the direct operator takes a piece from the production line, inspects it, fills out a checklist (which can vary by item), and places it in one container if it is deemed acceptable, or in another container if it is deemed scrap. Both containers are located on the machine.
- **Quality Control Inspection**: Every Y hours, the quality control inspector checks the pieces in both containers directly at the machine or in the quality office if dimensional checks are required.
- **Scrap Declaration**: After the inspection, the QC inspector will declare any detected scraps and manually assign them to the appropriate shift using a tablet. If the quality inspection is OK, the pieces are reintroduced into production. Otherwise, the operator must enter the detected non-conformity and the reason for the rejection.

Quality control is particularly relevant to DigInTraCE project, especially the scrap declaration phase because the pieces of information collected by the QC operator will be crucial for the AI algorithms in order to identify a cause-effect correlation and prediction of further rejected pieces.

At the end, the CLSC Tool will return to the ERP the following main information:

- Direct operators who have worked on the production order
- Work Center
- Indirect operators who have worked on the production order
- Work time per order:
    - Setup time
    - Start-up time
    - Processing time
- Downtime per order and reasons of the downtime
- Number of pieces produced per production order
- Number of scrap pieces per production order together with an explanation of scrap reason

Every production data is stored in the IoT layer and the CLSC Tool systems and can be shared with the DPP adopting Microsoft technologies like Data Factory or LogicApp, or by the mean of .csv files.

Considering the various interactions among the ERP system, Scheduling, MES, Iot Layer and AI algorithms, continuous improvement actions can be implemented to progressively reduce waste and thereby enhance efficiency, creating a virtuous cycle.

6. ML algorithms for anomalies detection and prevention

In this section we first define the anomalies detection and prevention problem, then we describe the expected inputs and outputs according to the dataset descriptions delivered by SIGIT, finally we provide a high-level description of the class of Machine Learning (ML) algorithms that are expected to be exploited.

6.1. Anomalies detection and prevention problem

The anomalies detection and prevention problems consist of creating, using a dataset of training historical data, a mathematical model able to detect or prevent, in real time, anomalies of the system using a streaming source of data compatible with those used for the training. The algorithm is divided in two phases: (1) training, where an historical dataset (not necessarily in run time) is exploited to generate the anomaly detection model; (2) validation, where runtime data, with the same characteristics of those used for the training phase, will be used to detect anomalies using the model generated in the training phase.

We will tackle this problem using an interdisciplinary approach, which appropriately exploits algorithms from Machine Learning and from Control Theory: such innovative approach is able to leverage the potentialities of supervised machine learning for data classification, as well as the mathematical background of control theory, specifically related to the Kalman filter well known method, capable of processing time series.

6.2. Expected dataset description

Hereby are enumerated some examples of expected dataset provided by SIGIT for each phase of the molding process. As illustrated in the tables and figures, the data extracted from the injection molding machine consist of physical variables extracted at specific sampling times for each cycle: as a consequence, for each produced piece time trajectories of such variables are available. This makes it critical to develop algorithms able to account for the system's dynamics via control theory, as well as machine learning algorithms able to classify nominal vs. defective behaviours. It is still to be verified whether it will be possible to associate, to each production cycle, a label indicating either "nominal" or "defective" piece. According to the availability of this information, the machine learning technique to be used substantially changes: In the next section we provide a list of tentative algorithms that can be exploited for such classification task in both cases.

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6.2.1. Filling phase

The filling phase dataset consists of main injection fill set data, main injection switch set data, actual screw position value, actual screw pressure value, as illustrated in details in Figure 4 and Table 5: Filling data descriptionTable 5.

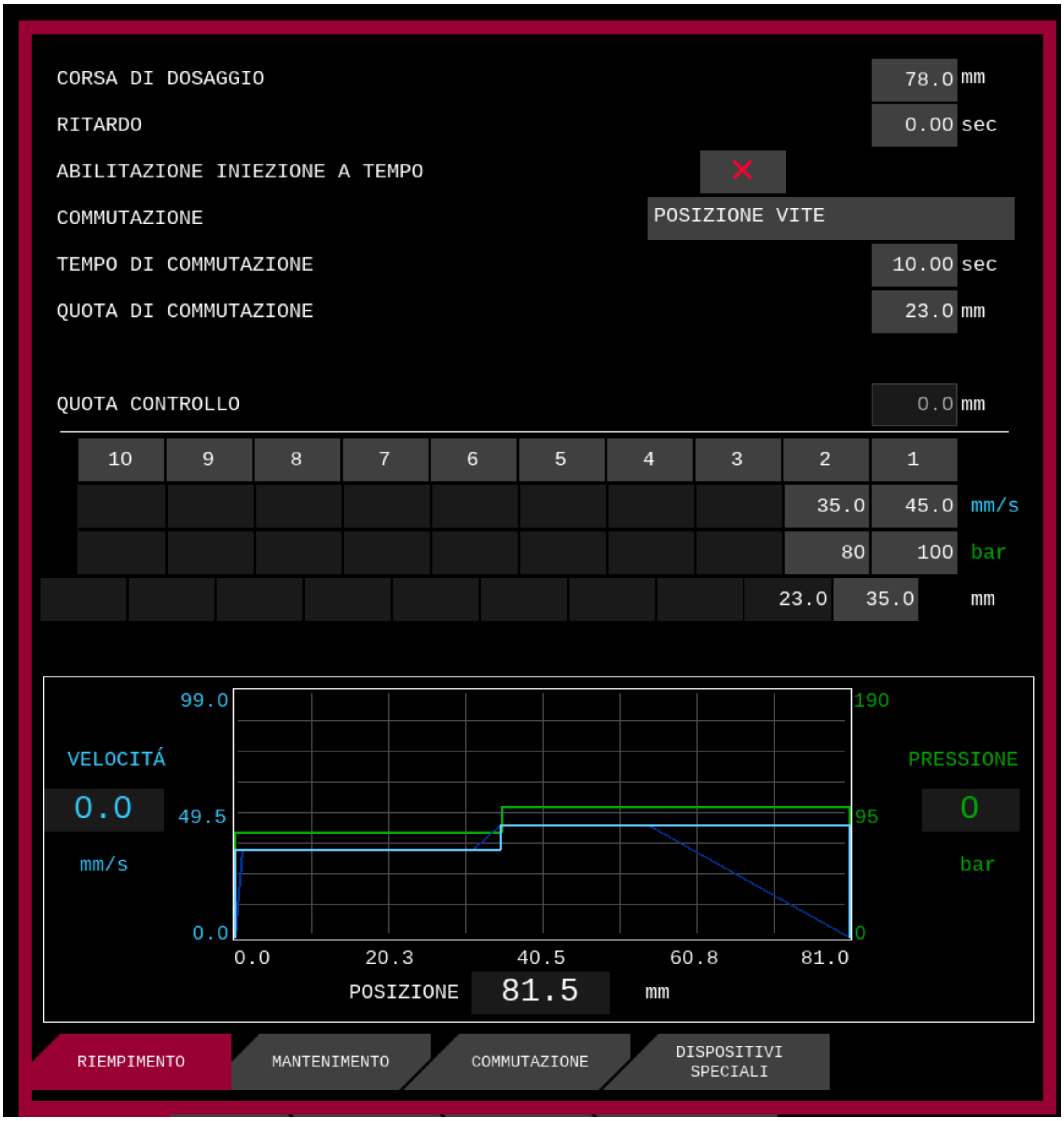

Figure 4: Filling data example

Table 5: Filling data description

Description	Property	Max	Data Type	Unit
Number of fill steps	R/W	10	Int16	

Step 1 fill profile speed	R/W		Float	mm/s
Step 2 fill profile speed	R/W		Float	mm/s
Step 3 fill profile speed	R/W		Float	mm/s
Step 4 fill profile speed	R/W		Float	mm/s
Step 5 fill profile speed	R/W		Float	mm/s
Step 6 fill profile speed	R/W		Float	mm/s
Step 7 fill profile speed	R/W		Float	mm/s
Step 8 fill profile speed	R/W		Float	mm/s
Step 9 fill profile speed	R/W		Float	mm/s
Step 10 fill profile speed	R/W		Float	mm/s
Step 1 fill profile pressure	R/W		Float	bar
Step 2 fill profile pressure	R/W		Float	bar
Step 3 fill profile pressure	R/W		Float	bar
Step 4 fill profile pressure	R/W		Float	bar
Step 5 fill profile pressure	R/W		Float	bar
Step 6 fill profile pressure	R/W		Float	bar
Step 7 fill profile pressure	R/W		Float	bar
Step 8 fill profile pressure	R/W		Float	bar
Step 9 fill profile pressure	R/W		Float	bar
Step 10 fill profile pressure	R/W		Float	bar
Step 1 fill profile position	R/W		Float	mm
Step 2 fill profile position	R/W		Float	mm

Step 3 fill profile position	R/W		Float	mm
Step 4 fill profile position	R/W		Float	mm
Step 5 fill profile position	R/W		Float	mm
Step 6 fill profile position	R/W		Float	mm
Step 7 fill profile position	R/W		Float	mm
Step 8 fill profile position	R/W		Float	mm
Step 9 fill profile position	R/W		Float	mm
Switch position	R/W		Float	mm
Switch type	R/W		Byte	
Dosage stroke	R/W		Float	mm
Switch time	R/W		Int32	ms
Current screw position	R		Float	mm
Instantaneous injection pressure	R		Float	bar

6.2.2. Holding phase

The holding phase dataset consists of main injection hold set data, actual screw position value, actual time value from start of holding, as illustrated in detail in the below Figure 5 and Table 6.

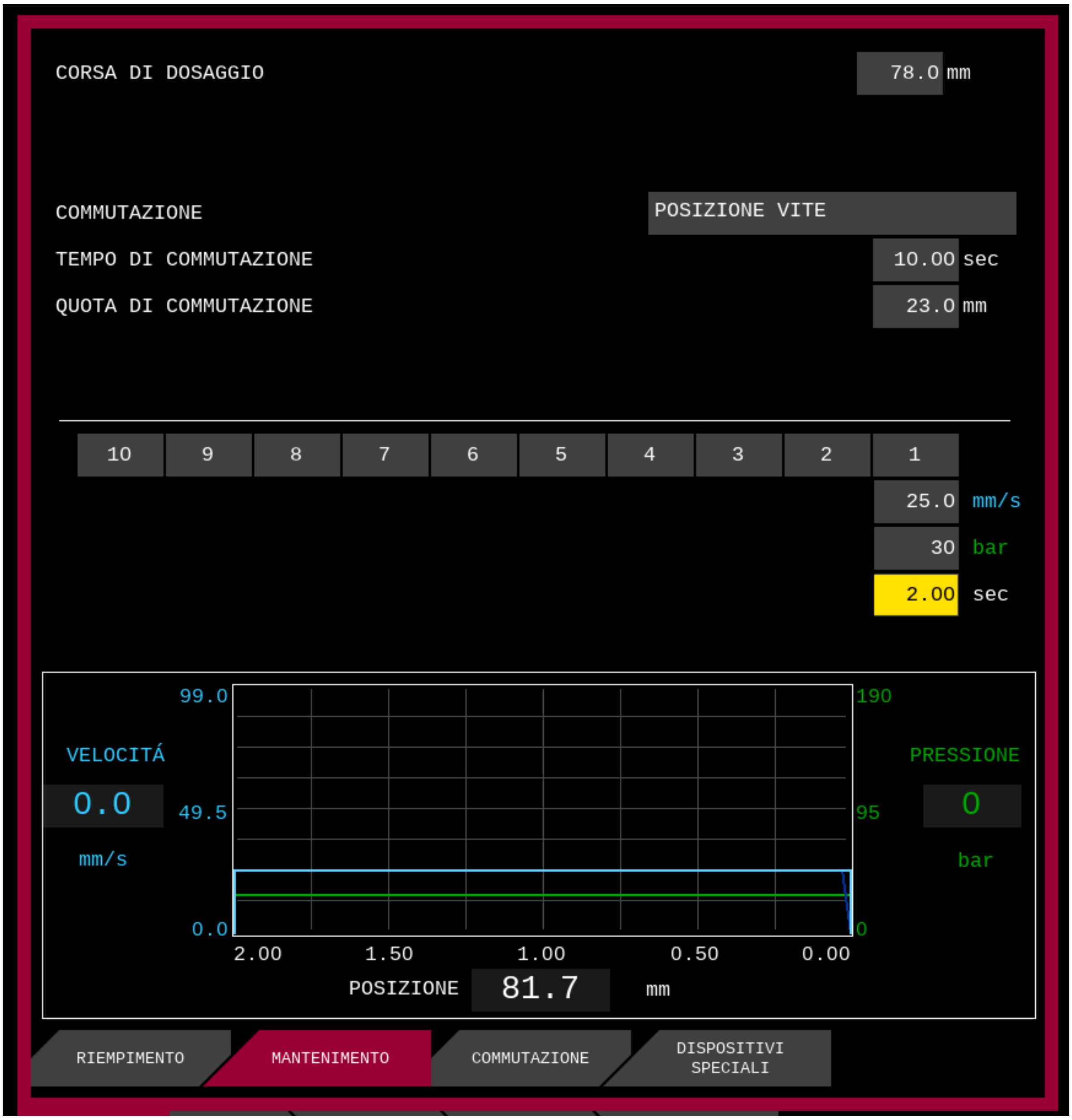

Figure 5: Holding data example

Table 6: Holding data description

Description	Property	Max	Data Type	Unit
Number of holding steps	R/W	10	Int16	
Step 1 hold profile speed	R/W		Float	mm/s
Step 2 hold profile speed	R/W		Float	mm/s
Step 3 hold profile speed	R/W		Float	mm/s

Step 4 hold profile speed	R/W		Float	mm/s
Step 5 hold profile speed	R/W		Float	mm/s
Step 6 hold profile speed	R/W		Float	mm/s
Step 7 hold profile speed	R/W		Float	mm/s
Step 8 hold profile speed	R/W		Float	mm/s
Step 9 hold profile speed	R/W		Float	mm/s
Step 10 hold profile speed	R/W		Float	mm/s
Step 1 hold profile pressure	R/W		Float	bar
Step 2 hold profile pressure	R/W		Float	bar
Step 3 hold profile pressure	R/W		Float	bar
Step 4 hold profile pressure	R/W		Float	bar
Step 5 hold profile pressure	R/W		Float	bar
Step 6 hold profile pressure	R/W		Float	bar
Step 7 hold profile pressure	R/W		Float	bar
Step 8 hold profile pressure	R/W		Float	bar
Step 9 hold profile pressure	R/W		Float	bar
Step 10 hold profile pressure	R/W		Float	bar
Step 1 hold profile time	R/W		Int32	ms
Step 2 hold profile time	R/W		Int32	ms
Step 3 hold profile time	R/W		Int32	ms
Step 4 hold profile time	R/W		Int32	ms
Step 5 hold profile time	R/W		Int32	ms

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Step 6 hold profile time	R/W		Int32	ms
Step 7 hold profile time	R/W		Int32	ms
Step 8 hold profile time	R/W		Int32	ms
Step 9 hold profile time	R/W		Int32	ms
Step 10 hold profile time	R/W		Int32	ms
Switch position				
Switch type				
Dosage stroke				
Switch time				
Actual time from start of holding				

6.2.3. Injection phase graph

The injection phase graph dataset consists of time curve (400 values), pressure curve (400 values), position curve (400 values), actual position curve (400 values), with the sampling frequency determined by the set trace time / 400 samples, as illustrated in detail in the below Figure 6 and Table 1.

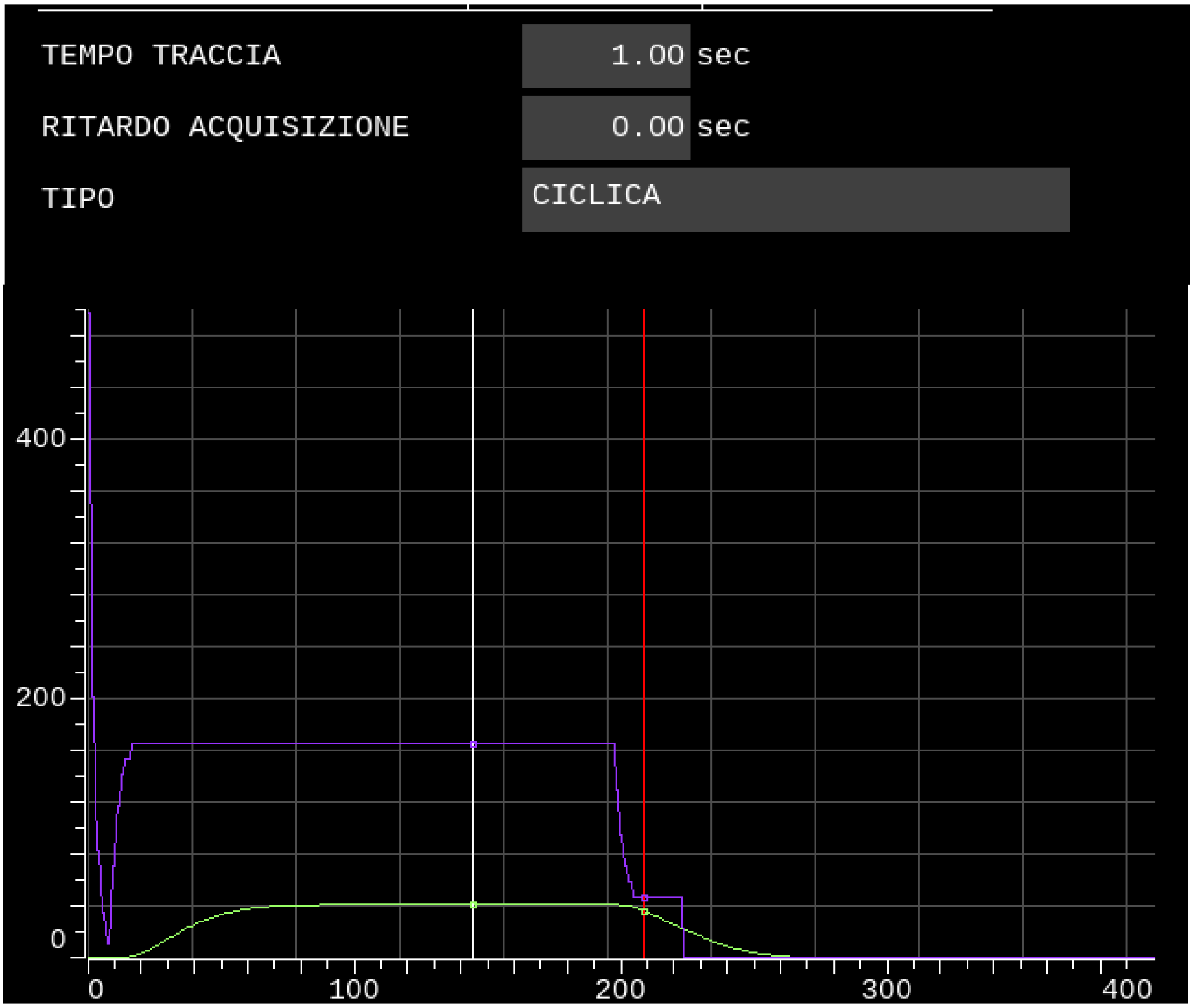

Figure 6: Injection phase graph data example

Table 7: Injection phase graph data description

Description	Property	Data Type	Unit
Sampling frequency	R	Int16	ms
Trace time	R/W	Int32	ms
Acquisition delay	R/W	Int32	ms
Number of samples	R	Int16	
Array of times	R	Float Array[400]	ms
Array of pressures	R	Float Array[400]	bar
Array of velocities	R	Float Array[400]	mm/s

Array of positions	R	Float Array[400]	mm

6.2.4. Dosing phase

The dosing phase dataset consists of main dosing set data, actual screw rotation value, actual back pressure value, as illustrated in detail in the below Figure 7 and Table 8.

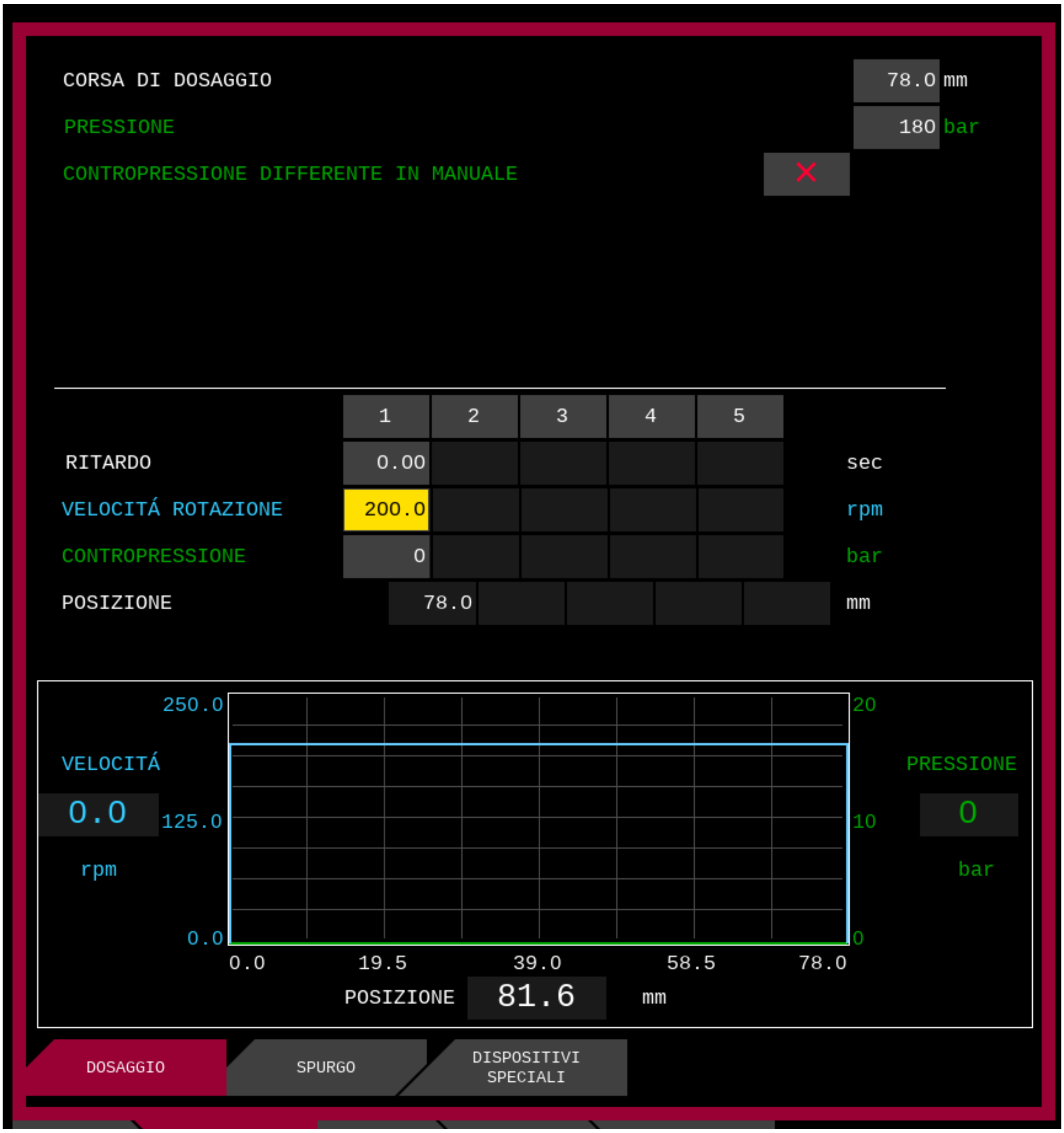

Figure 7: Dosing phase data example

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Table 8: Dosing phase data description

Description	Property	Max	Data Type	Unit
Number of dosing steps	R/W	5	Int16	
Step 1 dosing profile speed	R/W		Float	rpm
Step 2 dosing profile speed	R/W		Float	rpm
Step 3 dosing profile speed	R/W		Float	rpm
Step 4 dosing profile speed	R/W		Float	rpm
Step 5 dosing profile speed	R/W		Float	rpm
Step 1 dosing profile back pressure	R/W		Float	bar
Step 2 dosing profile back pressure	R/W		Float	bar
Step 3 dosing profile back pressure	R/W		Float	bar
Step 4 dosing profile back pressure	R/W		Float	bar
Step 5 dosing profile back pressure	R/W		Float	bar
Step 1 dosing profile position	R/W		Float	mm
Step 2 dosing profile position	R/W		Float	mm
Step 3 dosing profile position	R/W		Float	mm
Step 4 dosing profile position	R/W		Float	mm
Step 5 dosing profile position	R/W		Float	mm
Switch position	R/W		Float	mm
Switch type	R/W		Byte	
Dosage stroke	R/W		Float	mm

Switch time	R/W		Int32	ms
Current screw rotation	R		Float	rpm
Instantaneous back pressure	R		Float	bar

6.2.5. Molding phase

The molding phase dataset consists of data of mold opening position set, actual mold position value, actual closing force value, as illustrated in detail in the below Figure 8 and Table 9.

Figure 8: Molding phase data example

Table 9: Molding phase data description

Description	Property	Max	Data Type	Unit of Measure
Mold opening position	R/W		Float	mm
Actual mold position value	R		Float	mm
Actual closing force value	R		Float	ton

6.2.6. Cylinder temperature data

For each individual zone, for 2 injection groups, the protocol provides the data illustrated in detail in the below Figure 9 and Table 10.

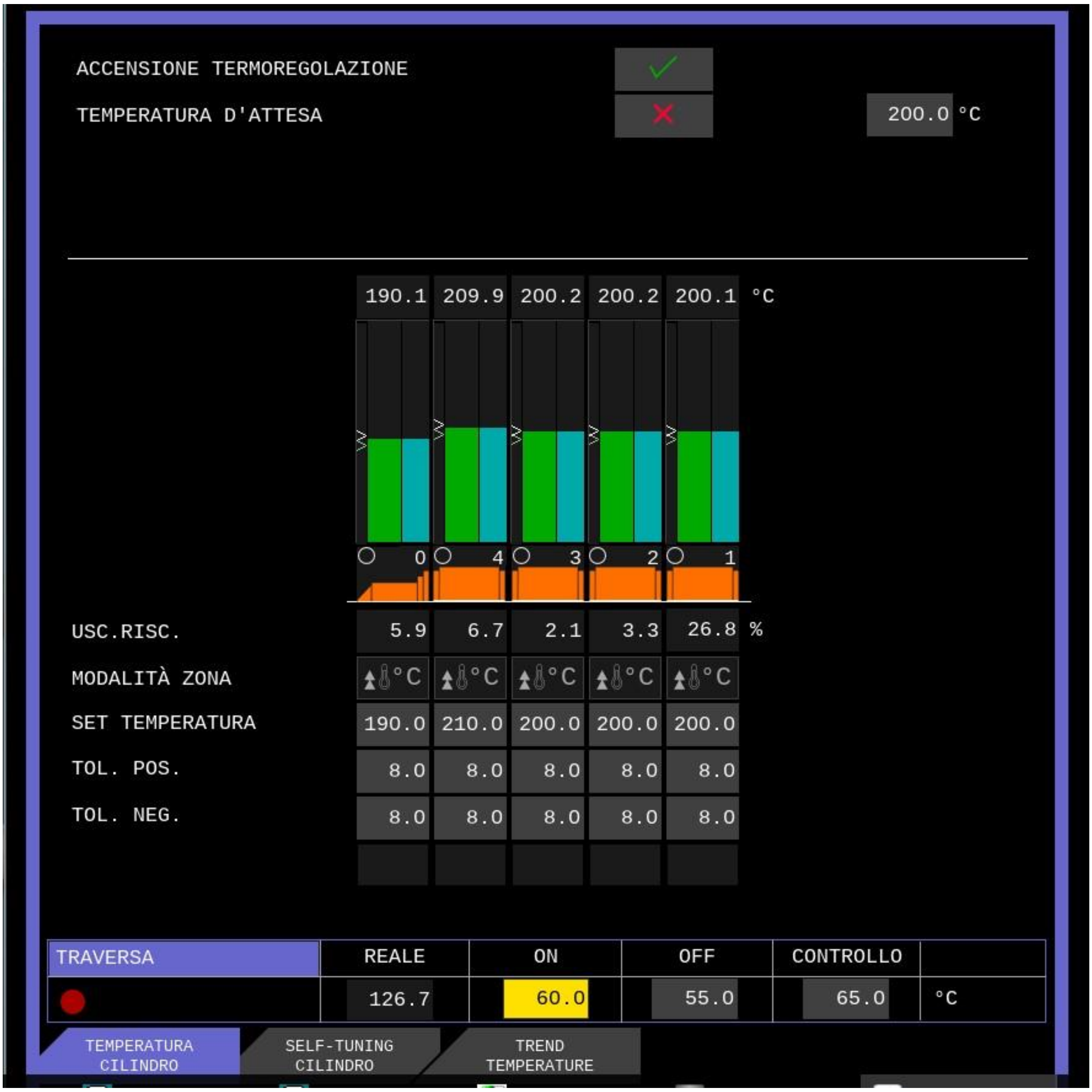

Figure 9: Cylinder temperature data example

Table 10: Cylinder temperature data description

Attribute	Value				
BrowseName	TemperatureZoneType				
IsAbstract	False				
References	**Node Class**	**BrowseName**	**DataType**	**TypeDefinition**	**Other**
Subtype of 0:*BaseObjectType* defined in OPC UA Part 5					
0:HasProperty	Variable	Index	0:UInt32	0:PropertyType	M, RO
0:HasProperty	Variable	Name	0:String	0:PropertyType	M, RO
0:HasProperty	Variable	IsPresent	0:Boolean	0:PropertyType	M, RO
0:HasProperty	Variable	Classification	TemperatureZone Classification Enumeration	0:PropertyType	O, RO
0:HasProperty	Variable	ControlMode	ControlMode Enumeration	0:PropertyType	M, RO
0:HasComponent	Variable	NominalTemperature	0:Double	0:AnalogItemType	M, RO
0:HasComponent	Variable	HighDeviationTemperature1	0:Double	0:AnalogItemType	O, RO
0:HasComponent	Variable	HighDeviationTemperature2	0:Double	0:AnalogItemType	O, RO
0:HasComponent	Variable	LowDeviationTemperature1	0:Double	0:AnalogItemType	O, RO
0:HasComponent	Variable	LowDeviationTemperature2	0:Double	0:AnalogItemType	O, RO
0:HasComponent	Variable	ActualTemperature	0:Double	0:AnalogItemType	M, RO
0:HasComponent	Variable	StandbyTemperature	0:Double	0:AnalogItemType	O, RO

6.2.7. Temperature of the mold data

For each individual zone, the protocol provides the data illustrated in detail in the below Figure 10: Temperature of the mold data exampleFigure 10 and Table 11.

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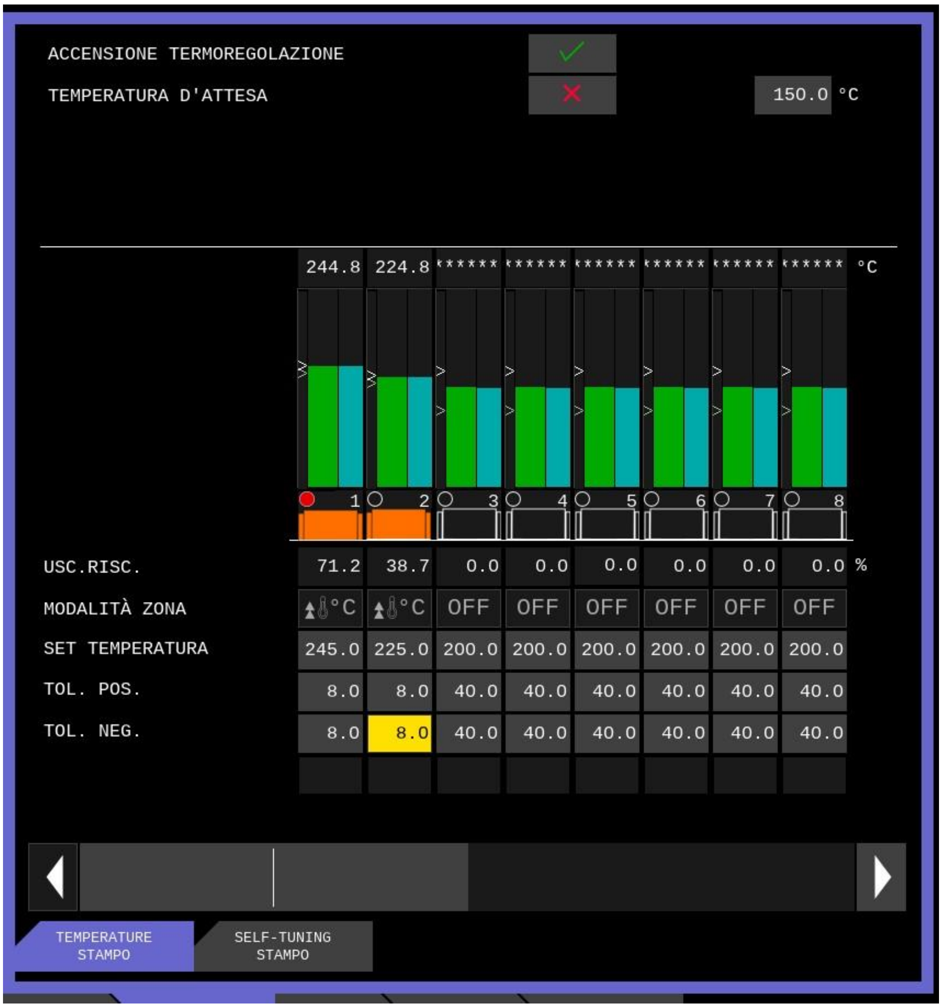

Figure 10: Temperature of the mold data example

Table 11: Temperature of the mold data description

Attribute	Value				
BrowseName	TemperatureZoneType				
IsAbstract	False				
References	**Node Class**	**BrowseName**	**DataType**	**TypeDefinition**	**Other**
Subtype of 0:*BaseObjectType* defined in OPC UA Part 5					
0:HasProperty	Variable	Index	0:UInt32	0:PropertyType	M, RO
0:HasProperty	Variable	Name	0:String	0:PropertyType	M, RO
0:HasProperty	Variable	IsPresent	0:Boolean	0:PropertyType	M, RO
0:HasProperty	Variable	Classification	TemperatureZone Classification Enumeration	0:PropertyType	O, RO
0:HasProperty	Variable	ControlMode	ControlMode Enumeration	0:PropertyType	M, RO
0:HasComponent	Variable	NominalTemperature	0:Double	0:AnalogItemType	M, RO
0:HasComponent	Variable	HighDeviationTemperature1	0:Double	0:AnalogItemType	O, RO
0:HasComponent	Variable	HighDeviationTemperature2	0:Double	0:AnalogItemType	O, RO
0:HasComponent	Variable	LowDeviationTemperature1	0:Double	0:AnalogItemType	O, RO
0:HasComponent	Variable	LowDeviationTemperature2	0:Double	0:AnalogItemType	O, RO
0:HasComponent	Variable	ActualTemperature	0:Double	0:AnalogItemType	M, RO
0:HasComponent	Variable	StandbyTemperature	0:Double	0:AnalogItemType	O, RO

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6.2.8. SPC

Statistical Process Control helps the user monitor and control the manufacturing process to ensure consistent product quality. The Figure 11 shows the data available from the press.

Figure 11: Statistical Process Control parameters

Considering that the page on the press remains the same, a leaf will be created for each parameter selectable from the list (not just those set on the page). The properties of the 18 parameters can be set. For each of the 18 set parameters, the following properties can be configured: Selected parameter, Deviation, Minimum limit, Maximum limit. At the end of each cycle, the generation of the *CycleParametersEvent* is planned, which contains the values acquired during the cycle related to injection and the mould. Additional parameters not covered by Euromap 77 will need to be added. Information sent at the end of each automatic cycle performed by the press will be those listed in Table 12.

Table 12: SPC data

Parameter	Description
Injection	
xx	Injection number
yy	Barrel temperature zone number
InjectionUnitCycleParametersd_xx/BarrelTemperatureZone_yy/ActualTemperature	Actual temperature of the individual zone
InjectionUnitCycleParametersd_xx/BarrelTemperatureZone_yy/Index	Index of the individual zone

InjectionUnitCycleParametersd_xx/BarrelTemperatureZone_yy/Name	Name of the individual zone
InjectionUnitCycleParametersd_xx/CushionVolume	Volume of material remaining in the barrel after injection and holding
InjectionUnitCycleParametersd_xx/DosingTime	Time taken to prepare material for the next injection
InjectionUnitCycleParametersd_xx/Index	Injection number
InjectionUnitCycleParametersd_xx/InjectionTime	Time required to fill the mould cavity
InjectionUnitCycleParametersd_xx/PlastificationVolume	Volume of material for the next injection
InjectionUnitCycleParametersd_xx/SpecificPressureMaximum	Maximum specific pressure on the material during injection
Mould	
yy	Mould temperature zone number
MouldParameters_01/BarrelTemperatureZone_yy/ActualTemperature	Actual temperature of the individual zone
MouldParameters_01/BarrelTemperatureZone_yy/Index	Index of the individual zone
MouldParameters_01/BarrelTemperatureZone_yy/Name	Name of the individual zone
MouldParameters_01/Index	Mould number (1)

Specific production machines for testing purposes had been chosen, particularly focusing on injection molding machines and they are shown in Figure 12.

Sites vs **Nr. Of Workcenters** MATRIX **already** connected

PLANT	NEGRIBOSSI	GMB PRESSE	TOYO MACHINERY & METAL	Delta Robotics	DT INNOVATION DEVELOPMENT TECHNOLOGY
San Giustino	13		1	2	1
Cambiano		14			
Lacedonia	11				
Calatayud	21				
Kragujevac	27				

Sites vs **Nr. Of Workcenters** MATRIX **not yet** connected

PLANT	NEGRIBOSSI	GMB PRESSE	S.L.M. Second life machinery	Delta Robotics	DT INNOVATION DEVELOPMENT TECHNOLOGY
Atessa	17				
Monte San Vito	19		5		
Tangeri	9	8			
Skoczow	38				
Czechowice	12		9		
Cugir	19		7		

Current data sampling frequency to the datacenter

EUROMAP 63	OPC UA	Modbus
20 sec	10 sec	10 sec

Figure 12: SPC Work centers and allowed sampling frequencies

6.3. Machine Learning algorithms

We now provide a general overview of several supervised learning methods to predict the outcome based on a given input in different scenarios. In case there will be no availability of a label “nominal” or “defective” associated to each produced piece, in addition to such supervised learning methods there will be need to exploit “fault detection” algorithms from control theory, such as the well-known Kalman filter.

The inputs are called independent variables or features, whereas the outputs are called dependent variables, response variables or targets. In simple words, for a known output, the known inputs are taken to fit an unknown function, so we are trying to approximate a function using this learning method. Mathematically, Input variables à Function (Input variables) à Output. Now, let us look at different supervised learning techniques below.

K-Nearest Neighbor (KNN): The basic working principle relies on similar data points showing identical behaviour. Since this algorithm works locally, it effectively identifies patterns in varying datasets. 'K' is a parameter that represents the number of nearest neighbours considered when making predictions. Therefore, the selection of 'K' influences the algorithm's performance by balancing bias and variance. 'K' is also called a hyperparameter, along with a distance metric (Euclidean distance, Manhattan distance, Minkowski distance), which is another hyperparameter. It specifies various methods for calculating the distance between the data points. KNN differs from other learning methods in its simplicity and lack of explicit training phases. It uses a copy of the training data to make predictions, sometimes called a lazy algorithm. It is simple and easy to implement as it is non-parametric, assumes no specific data distribution, and possesses a minimal training phase. For large datasets, it is computationally expensive and sensitive to irrelevant features, and optimal 'K' selection can impact performance.

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Support Vector Machine (SVM): This algorithm can identify optimal hyperplanes that effectively separate the data points in the feature space. It maximizes the margin between different classes and approximates the regression function in regression. 'C' is a regularization hyperparameter that balances the trade-offs between a smooth decision boundary with a higher value of 'C 'and an accurate classification of training points with a low 'C'. The kernel trick enables SVM to identify non-linear decision boundaries by implicitly mapping data into higher-dimensional spaces. Epsilon determines the accepted error for the regression model, affecting support vectors' margin width. SVMs optimize the margin, which sets them apart from other learning techniques. So, they are effective in scenarios where clear class separation is needed. SVM is effective in high-dimensional spaces and versatile using the kernel trick; therefore, it is robust and can be overfitted using optimal regularization. SVM is sensitive to noisy data and computationally costly for a large dataset. It is also highly dependent on the hyperparameters.

Decision Trees: Recursive partitioning is the working principle behind decision trees, where the dataset is split into subsets based on feature conditions. Each partition represents a decision node, and the loop continues until a stopping criterion is met. The nodes represent decision points, and the leaves provide the final predictions. The conditional nodes guide the partition process. Maximum depth limits the number of decision nodes in a tree, whereas a deeper tree captures complex relations but is prone to overfitting. The minimum sample split specifies the minimum number of samples required to split an internal node where a higher value keeps check on creating small and noisy splits. The minimum sample leaf specifies the number of samples required to make a leaf node, affecting the final predictions' coarseness. The criterion specifies the function used to measure the quality of a split, which can be "gini" or "squared error" based on the type of problem. Compared to other ensemble methods, like random forest and gradient-boosted trees, which are stand-alone methods, the decision tree is prone to overfitting because it constrains tree growth. It also is not practical to predict by generalizing on unseen data. It is simple to understand and visualize, captures non-linear relationships well, and requires minor data for training. For complex relationships, the decision tree needs more expressiveness.

Random Forest: As the name suggests, the random forest builds a predictive model by making multiple decision trees. From feature selection to data sampling, the process is truly random, helping mitigate the effects of overfitting. The decision trees created are independent, and their predictions are averaged by voting or averaging. The number of trees equals the number of decision trees in the forest; more trees increase performance, but after optimal is reached, it leads to diminishing returns. Maximum tree depth is the depth for each decision tree, and deeper trees capture more complex relationships but come with overfitting. Feature subset size defines the number of selected features for each split in a decision tree. This randomness increases the diversity among the trees. A minimum sample split is used to split an internal node, but a higher value prevents the creation of small and noisy nodes. Criterion is used to measure the quality of the split, the same as the decision tree. Random forest combines multiple weak learners to create a robust model, mitigating the risk of overfitting and thus improving accuracy. The weak learners contribute equal weight to the final predictions. Random forest is effective in handling large datasets. However, it needs more interpretability in complex models and is resource-intensive for large datasets. It is also sensitive to noisy data.

Gradient Boosted Trees (GBT): GBT is a sequential method. It creates a prediction algorithm by adding the decision trees sequentially and correcting the errors of the previous ones. Intrinsically, the algorithm minimizes a loss function by optimizing the model fit to the training data. These boosting iterations define the number of trees added to the ensembles, and the learning rate controls the contribution of each tree. Therefore, balancing these parameters is crucial for getting a well-optimized model. A lower learning rate requires more trees to perform similarly but might enhance generalization. Increasing the number of trees improves the performance; the depth of trees captures more complex relationships but may lead to overfitting. A sub-sample uses a fraction of the training data to fit each tree, whereas a lower sub-sample value introduces randomness and can prevent overfitting. The loss function defines the error measurement that needs minimization during training, such as mean squares or deviations. GBT focuses on correcting errors in the existing ensembles; it provides high productive accuracy and handles non-linear relationships. At the same time, it is sensitive to noisy data, requires explicit tuning of the hyperparameters, and requires much longer training time due to its sequential approach.

Multi-layer Perceptron (MLP): In MLP, which tries to mimic the human brain, input data is passed through layers of interconnected nodes, and an activation function is applied to introduce non-linearity. Then, the nodes learn from the data by adjusting the weights and biases through backpropagation, optimizing the model's performance. Input layers receive the input features, hidden layers are responsible for learning complex patterns, and the output layer produces the model's final output. The learning rate determines the step size while updating the weights. A lower learning rate promotes stability, but the convergence will be slower. On the other hand, larger values lead to oscillations and overshooting. The choice of hidden layers impacts the network's learning capacity, but more profound architecture captures complex relationships but increases the risk of overfitting. The number of nodes per layer affects the model's expressive behaviour; more nodes allow the network to learn more complex features. Activation functions like "ReLU", "sigmoid", or "tanh" introduce non-linearities in the hidden layers. Batch size defines the number of data points used in each training iteration, where a significant batch speeds up the training but needs more memory. Epochs refer to the number of times the entire dataset is passed through the network; if it is less, it may lead to underfitting. MLP can learn complex non-linear relationships, is versatile and applicable to various tasks, and can automatically learn valuable features from the raw data. However, it is prone to overfitting with large architectures, needs extrinsic tuning of the hyperparameters, and the training is usually computationally intensive, especially for large datasets and complex architectures.

Naïve Bayes: Naïve Bayes is a probabilistic classifier that applies Bayes' theorem with the assumption of independence between every pair of features. Despite its simplicity and the strong independence assumption, it performs well in various real-world situations, especially for text classification tasks. The algorithm computes the posterior probability of a class given the input features and predicts the class with the highest posterior probability. This calculation involves prior probabilities of the classes and the likelihood of the features given the class, assuming feature independence. There are different types of Naïve Bayes classifiers based on the data distribution:

- Gaussian Naïve Bayes assumes that the features follow a normal distribution.
- Multinomial Naïve Bayes is suitable for discrete data and is commonly used for text classification.
- Bernoulli Naïve Bayes is useful when binary or boolean features are present.

Naïve Bayes is computationally efficient, requires a small amount of training data, and can handle high-dimensional data well. However, it assumes that all features are equally important and independent, which is rarely true in practice. Despite this, it often performs surprisingly well and can serve as a strong baseline for text classification tasks and other applications.

Generalized Linear Model (GLM): Generalized Linear Models (GLM) extend linear models to accommodate non-normal distributions of the response variable by linking the mean of the response variable to a linear predictor through a link function. The three main components of GLMs are:

- Random Component: Specifies the probability distribution of the response variable (e.g., normal, binomial, Poisson).
- Systematic Component: Represents the linear predictor, a linear combination of the input features.
- Link Function: Connects the expected value of the response variable to the linear predictor. Standard link functions include the identity link (for linear regression), logit link (for logistic regression), and log link (for Poisson regression).

GLMs are flexible and can model various data distributions, providing a broad framework for many statistical models. They are widely used in fields like economics, biology, and epidemiology. However, GLMs require careful selection of the link function and the distribution of the response variable. Mis-specification can lead to poor model performance.

Logistic Regression: Logistic regression is a type of GLM used for binary classification problems. It models the probability of the target variable belonging to a class by fitting a logistic function (sigmoid) to the linear predictor. Key hyperparameters and considerations include:

- Regularization Parameters: L1 and L2 regularization (controlled by the parameter C in many implementations) helps prevent overfitting by penalizing significant coefficients.
- Solver: Different solvers like "liblinear", "saga", and "lbfgs" can be used for optimization, each with trade-offs in terms of speed and convergence.

Logistic regression is interpretable, easy to implement, and performs well on linearly separable data. It can also extend to multiclass classification problems (one-vs-rest or multinomial logistic regression). However, it may need help with non-linear relationships and requires careful feature engineering to perform well on complex datasets.

Fast Large Margin: Fast large margin (FLM) classifiers, also known as large margin nearest neighbour (LMNN) algorithms, optimize classification by maximizing the margin between classes while incorporating the speed and simplicity of instance-based learning methods. The main idea is to learn a distance metric that minimizes the distance between similar instances and maximizes the margin between different classes. This is achieved through a combination of:

- K-nearest neighbours: Ensuring similar instances are close together.
- Large margin principles: Ensuring different classes are well-separated.

FLM algorithms often involve learning a Mahalanobis distance metric, which adapts the feature space to improve classification accuracy. This is typically formulated as a convex optimization problem. FLM's advantages include its ability to handle high-dimensional data and maintain fast prediction times due to its reliance on instance-based learning. However, it can be computationally intensive during the training phase, especially for large datasets, due to the need to solve an optimization problem. Additionally, selecting the appropriate number of neighbours and regularization parameters is crucial for optimal performance.

7. Overall integration to implement the reuse optimization process

This chapter aims to describe the steps that the waste will do in order to increase its reusability and therefore its sustainability. Moreover, it serves to clarify what has been explained in the previous paragraphs, it provides insights concerning the physical and informational flows, and how the various technologies interact.

The field chosen for the project is that of WEEE, for which the upstream supply chain is constituted by local collection at ecocenters. The ecocenters collect end-of-life equipment throughout Italy at the municipal level. Any EOL product that

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arrives at an ecocenter becomes waste, regulated by many restrictive laws aimed at preventing improper use or reuse. Only companies with the proper authorization can manage it. Collecting is not a scope of the Italian demo for DigInTraCE. For more information the reader can refer to Italian D.Lgs 152/2006, D.M. 13/05/2009, D.M. 08/04/2008 and related norms and laws.

According to Italian regulation [i] the WEEE Coordination Center – CDCRAEE[ii] - is a private consortium imposed by the government authority that leads and optimizes the collection and management of WEEE. It works under the EU directive 2012/12/EU.

In Italy, the WEEE Coordination Centre is the reference point for all those involved in the supply chain of waste from electrical and electronic equipment (WEEE). The WEEE Coordination Centre is responsible for optimizing the management of WEEE in Italy, in fact it directs the collection of electronic waste by Italian municipalities to achieve European collection targets to protection and improvement of the quality of the environment and human health. Disposal takes place through Collective Systems, consortia that deal with the collection, transport, treatment and recovery of WEEE, in compliance with the indications of the law and the rules established by the WEEE Coordination Center.

The Collective Systems manages the transport of waste to a certified and authorized treatment plant.

For the Italian Demo Case, the treatment and selection process considered is currently carried out by a partner of SIGIT (sources of the materials for the demo), with the same will be carried out full-scale final tests including sensing and sorting advanced technique performed by IRIS and ICCS.

The raw materials recycled are transformed into Second Raw Materials inside the same facility and SIGIT is allowed by Italian authorization for this process.

The materials output from the selection and detection process will be tested later by Sigit in its production processes.

The scope of the recycling process, as described, is the production of Secondary Raw Materials – SRMs - based on pure polymer and/or polymeric compounds, formulated from high percentages of materials recovered from WEEE. The improvement in terms of kind of polymeric compounds processed and the efficiency of the process are part of scope of the study.

The material flow diagram shown in Figure 13 describes the project in-scope steps that the material will do among the different actors.

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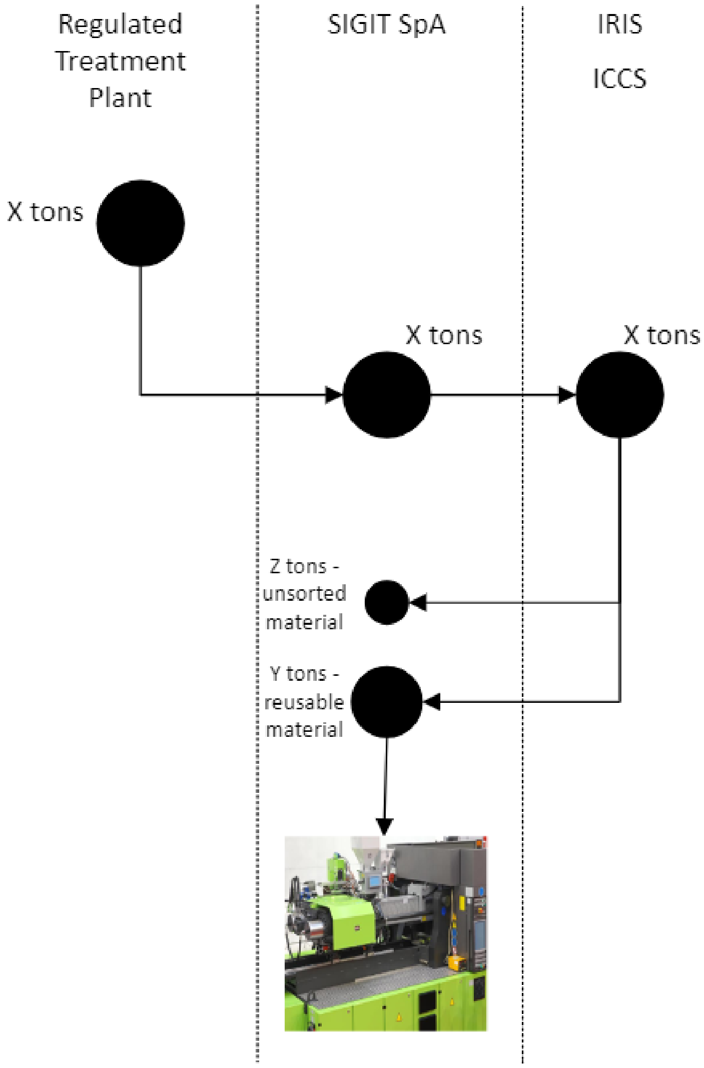

Figure 13: Material flow

As a first step, X tons of WEEE undergoes preliminary treatment at specific facilities in compliance with Italian law, before being sent to SIGIT Spa. After performing checks and filtering, SIGIT Spa will send heavy plastic flakes to IRIS and ICCS for their further sensing and sorting analysis. It is anticipated that the detection process will not achieve 100% efficiency due to the challenging separation of certain flakes resulting from their composition. Consequently, while X tons of material is sent, only Y tons can be considered reusable and suitable for reintroduction into production. The remaining Z tons of material will be sent to SIGIT Spa in order to have a closed loop traceability and ownership of waste.

Upon receipt and reintegration of the reusable material into production, its presence and inventory are managed by the ERP and CLSC Tool. Based on the finished products to be manufactured, the material is called from their bill of materials and subsequently delivered to the presses where a specific production order is scheduled. Throughout the production process, real-time data collection managed by the MES, supplemented by the IoT layer, enables AI algorithms to predict anomalies and production drifts. When such events occur, the algorithms trigger an event to the Scheduler module, which can either generate a

maintenance order for a particular press or send warnings to devices on the line, thereby supporting the operator. Additionally, to ensure traceability, production data can be dynamically transmitted to the DPP.
In the diagram represented in Figure 15, all the mentioned elements can be seen working together.

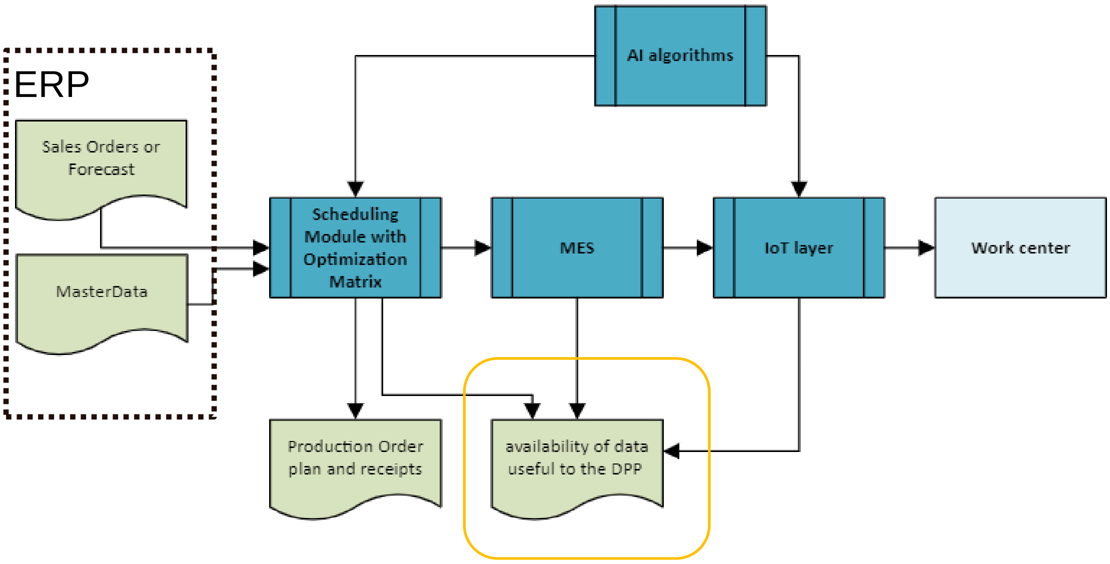

Figure 14: The integrated solution diagram

The DPP becomes a unique "object" where relevant data related to the entire supply chain can be stored and queried, guaranteeing complete traceability. The in-depth technical details are provided in D2.1 and D2.4.

Unfortunately, due to the unforeseen SIGIT's termination, the completion of the task to which this deliverable refers has been postponed, obliging the DigInTraCE Consortium to reorganize and implement the mitigation actions planned for this risk.

7.1. Mitigation action and next steps

The Consortium promptly united to find a replacement for SIGIT, so that the planned activities could be managed in the best possible way. The most challenging aspect is finding a new partner interested in producing finished products to sell to their final customers in recycled material. Nonetheless, SIGIT is in the automotive sector, which, although highly regulated, is not as strictly regulated as the food sector, for example, where the constraints are even more stringent.
Once a new partner is approved, the project team will conduct a gap analysis of the differences between the two scenarios. By changing the finished product to be

produced, it is very likely that the material in focus will also change, and the process for optimizing its reuse will need to be studied.
Nevertheless, with the approval of a new partner and through thorough discrepancy analysis, the project team is poised to adapt and optimize the reuse process effectively, ensuring continued progress and success in achieving the DigInTraCe objectives.

Despite SIGIT's exit, the activities conducted thus far have enabled partners to perform initial analyses on plastic materials and test their technological tools, which will also be applied in the new future scenario.
The departure of SIGIT has necessitated a reevaluation of project dynamics, particularly in the context of plastic material analysis and technological tool testing. Prior to SIGIT's exit, significant groundwork had been laid, allowing partners to initiate crucial assessments and trials. These activities have served as foundational steps in understanding material characteristics, exploring processing capabilities, and refining methodologies tailored to project objectives.
Partners have leveraged this early phase to validate and optimize their technological frameworks designed for plastic material analysis.

Moving forward, the project is poised to transition seamlessly despite the setback posed by SIGIT's departure. The momentum gained from early analyses and tool testing positions partners to pivot effectively towards new collaborative arrangements. The resilience demonstrated in adapting workflows and recalibrating strategies underscores the consortium's commitment to project continuity and success.

Furthermore, the experience gained from initial analyses provides a robust foundation for comparison and benchmarking in the revised project landscape. As partners explore opportunities to onboard a new collaborator, they are equipped with insights and data-driven approaches honed through rigorous testing and validation. This proactive approach ensures that future endeavors in plastic material analysis and technological advancement remain aligned with project objectives and stakeholder expectations.

While SIGIT's exit introduced challenges, it also catalyzed a phase of introspection and adaptation within the consortium. The collaborative efforts undertaken thus far have not only fortified technical capabilities but also reinforced the consortium's resilience in navigating unforeseen circumstances. By leveraging early successes in material analysis and technological tool development, partners are primed to forge ahead with confidence, ensuring continuous advancement and innovation in the project's pursuit of sustainable solutions.

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8. Conclusions

The study on the reuse optimization of plastic parts and components reveals several key findings and provides actionable recommendations to enhance reuse processes. This comprehensive analysis underscores the significance of various types of plastics, their properties, and their potential for reuse, highlighting the crucial role of closed-loop supply chains (CLSC).

Moreover, the implementation of modern sorting technologies significantly improves the identification and separation of different plastic types, ensuring higher purity and quality of recycled materials. The study emphasizes the need to optimize the quality and consistency of SRMs to meet industry standards, enhancing their application in new products and supporting sustainable manufacturing practices. Implementing rigorous quality control measures and adhering to customer-specific requirements (CSR) is crucial to ensure the reliability and performance of reused components.

The use of the Closed Loop Supply Chain Tool (CLSC Tool) and the Digital Product Passport (DPP) streamlines processes, tracks material flows, and improves transparency and traceability throughout the lifecycle of plastic parts. Promoting the reuse of plastic components supports environmental sustainability by reducing waste and conserving resources. It also offers economic advantages by lowering material costs and creating new business opportunities in recycling and manufacturing sectors.

Therefore, a comprehensive approach that combines technological advancements, stringent quality control, and industry collaboration is essential to optimize the reuse of plastic parts and components. By adopting these strategies, industries can contribute to a more sustainable and circular economy, aligning with global efforts to reduce plastic waste and promote resource efficiency.

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9. References

[i] D.Lgs 49/2014 art.33 and 34
[ii] https://www.cdcraee.it/