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DIGITAL VALUE CHAIN INTEGRATION TRACEABILITY FRAMEWORK FOR PROCESS INDUSTRIES FOR CIRCULARITY AND LOW EMISSIONS BY WASTE REDUCTION AND USE OF SECONDARY RAW MATERIALS

D5.4

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List of abbreviations

Abbreviation	Definition
MDF	Medium density fibre board
PB	Particle board
PEFC	Program for Endorsement of Forest Certification

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1. Introduction

The present report constitutes deliverable 5.4 “Wood by-products sorting and characterization for process optimization v1” within the framework of the DigInTraCE project. The following activities refer to WP5 “Technologies for secondary materials upgrade and process optimization” and specifically to task 5.3“Wood by-products sorting and characterization for process optimization)”.

This Deliverable involves characterization and classification requirement in terms of by-products being directed towards specific valorisation, and data analysis correlating secondary resource’s properties with the final products´ quality, being the first version of the Deliverable 5.5. “Wood by-products sorting and characterization for process optimization FINAL”.

WP5 aims to achieve three main objectives, the second of them includes the by-products sorting and characterization processes and technologies to be developed for the 2 wood-based demonstrators, for which the outputs of T5.3 are crucial.

This report includes the study of:

- Selection of wooden by-products
- Machine vision-based wood re-design toolkit
- Novel sensing and sorting techniques

2. Selection of wooden by-products

2.1. Wood characteristics

Most of the wood used in the different manufacturing lines of the company ASTI is extracted from the forests near the company, in the region in which ASTI is located, looking for a “zero kilometre” supply of materials. The felling is very selective: for every tree felled, another is planted. Two quality certifications guarantee this care of the forests: the PEFC certificate and the Ecolabel, awarded by the European Union, complying with a sustainable forest management.

The wood used by the company ASTI is radiata pine (*Pinus radiata D. Don*). Physical and mechanical data are stated in the table.

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Table 1: Properties of radiata pine virgin material12

Characteristic	Value
Density (kg/m3)	Around 400-500
Compression strength (N/m2)	42-55
Modulus of elasticity (MPa)	8.600-11.000
Bending resistance (MPa)	75-100
Shrinking	Radial: 3.4-4,3%, Tangential: 5,7-7%, Longitudinal around 0,7% Volumetric: 9,6-10.7%

Wood is an anisotropic material, and the different cuts behave in a very different way. The change in radial direction is approximately half compared to the tangential direction. Longitudinal changes are very low.

Upgrading the wood wastes of sawmill and furniture companies considering them as a relevant source of secondary resources, avoids forest harvesting. New solutions are necessarily linked to the obtaining of reliable raw materials of the whole production chain to produce products The main obstacle to wood subproducts recycling is the presence of non-wood substances and pollutants like paint, halogenated compounds and wood preservatives in a significant proportion. As a result, much less waste wood is recycled than is used for energy. Better knowledge of wood waste composition and quality and improvements on current sorting techniques are essential. Considering the quality of the by-product, there are different regulation options where residues are divided into classes depending on their degree of impurities. The Directive on waste (2008/98/EC) sets the basic concepts and definitions related to waste management such as definitions of waste, recycling, and recovery. and wastes are identified in the European residue list[3]There are several classification options and there is a Catalogue of wood waste classification in the UNECE region[4] Each country has different division of wood waste or does not use any. So, there are different national classifications of wood by-products[5]

- For example, Netherlands use classification with three grades (A, B, C). Grade A includes only clean wood (unpainted and untreated). .Grade B includes painted, varnished and glued wood) and Grade C impregnated being treated timber (NL Agency, 2013)
- .Other known national classifications example is a German waste regulation, that transposes the European Waste Framework Directive into national law “the Circular Economy Law” [6](BGBl. 2012, 212). The recovery and disposal of wood waste is regulated by the Waste WoodOrdinance[7] (BGBl. I 2002, 3302). The Ordinance contains a classification with four categories.

[1] (PDF) Some physical and mechanical properties of wood of Fast-growing tree species eucalyptus (Eucalyptus grandis) and radiata pine (Pinus radiata D.Don) (researchgate.net)

[2] (PDF) Some physical and mechanical properties of wood of Fast-growing tree species eucalyptus (Eucalyptus grandis) and radiata pine (Pinus radiata D.Don) (researchgate.net)

[3] *European Commission DECISION - of 18 December 2014 - Amending Decision 2000/ 532/ EC on the List of Waste Pursuant to Directive 2008/ 98/ EC of the European Parliament and of the Council; 2014;*

[4] *https://unece.org/sites/default/files/2021-03/ece-tim-efc-wp2-2021-inf-5.pdf*

[5]*https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5bf1792ce&appId=PPGMS*

[6] *https://www.gesetze-im-internet.de/krwg/BJNR021210012.html*

[7] *https://www.gesetze-im-internet.de/altholzv/AltholzV.pdf*

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Table 2: Waste wood categories in Germany according to the Waste Wood Ordinance

Category	Definition
AI	Waste wood in its natural state or only mechanically processed which, during use, was at most insignificantly contaminated with harmful substances
AII	Bonded, painted, coated, lacquered or otherwise treated waste wood with no halogenated organic compounds in the coating and no wood preservatives
AIII	Waste wood with halogenated organic compounds in the coating, with no wood preservatives
AIV	Waste wood treated with wood preservatives as well as other wood waste which, due to its contamination, cannot be assigned to waste categories AI, AII or AIII, with exception of waste wood containing PCBs
Wood waste containing PCBs	Waste wood which constitutes waste wood containing PCBs within the meaning of the PCB/PCT Waste Ordinance[8]

Sources: Annex III Waste Wood Ordinance; Reindahl Andersen et al., 2018

Wood products and furniture manufacturers generate the cleanest wood waste in form of sawdust, offcuts, and sand dust. The industrial wood by-products extracted from ASTI activities are free of any contaminant because they come from virgin wood and all the mechanization operations are made before any activity of painting, joining or any treatment.

Being free of toxic chemicals. No selection or sorting related to this aspect is necessary and the efforts are all focused on size matters, aspect and geometry. .

2.2. Wood by-products in ASTI

The general approach to the diagram of by-products generation, inside ASTIs manufacturing line is shown in the following Figure:

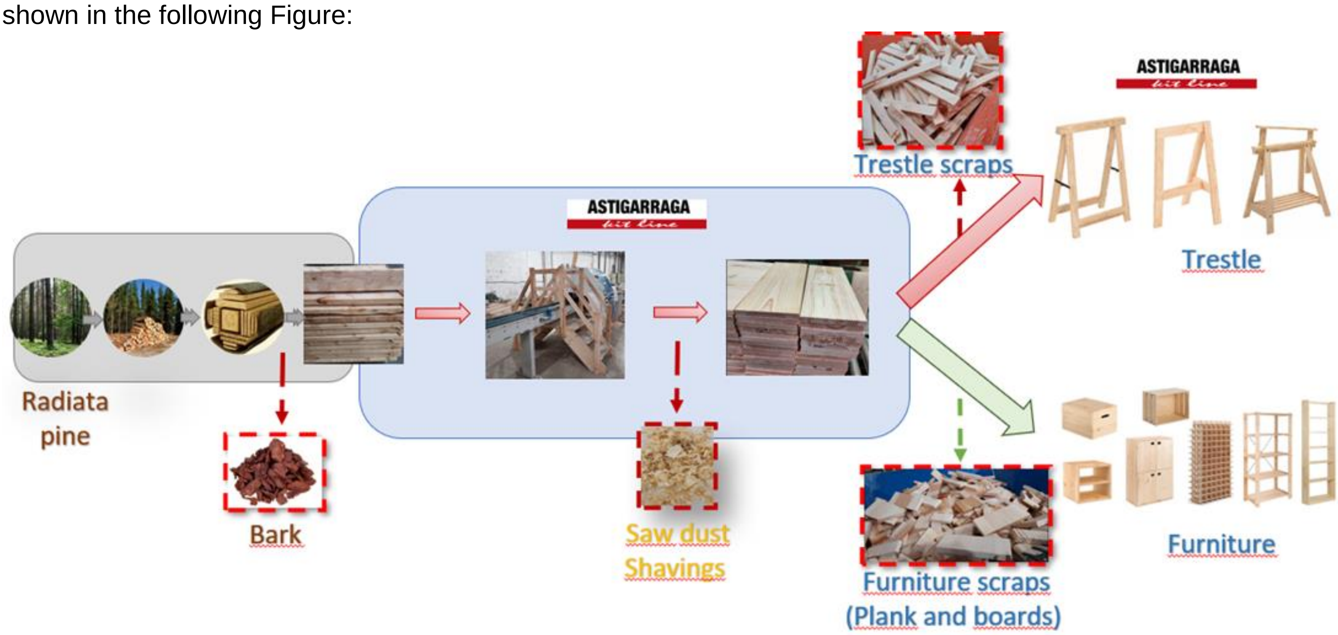

Figure 1: General approach to ASTU´s by-products generation

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At the company`s sawmill the logs are turned into uniform planks. Before going on to the manufacturing process, the wood is left to dry in the open air for three months. This natural drying or airing reduces the moisture content of the wood and a further step in the drying machine reduces it to 10-15%. After, stabilisation planks are cut. The cutting machine cuts the exact measurements (furniture and trestles), leaving everything ready for assembly.

The annual timber used is estimated at 33.800 Ton/year. There are two different steps where by-products appear. The first one is the sawmill step, and in the debarking process a 9% of the initial log is derived to bark, taken as one of the by-products fractions to be studied with 3.042 Ton/year. The actual use of this by-product is gardening and mulching.

Table 3: Retained wood and generated wood by-products

Annual wood incomes (sawmill)	Annual Wood mass retained in final products
33.800 Ton	10.647 Ton (31,5 %)

In a second transformation step, dry planks are cut to the size and thickness required for the furniture to be manufactured under a digitally controlled process. Then, new valuable by-products are generated from the dry planks: Scraps, Sawdust, Shaving and Sanding dust.

- Scraps (13,4%) accounting for 1.944Ton and devoted to a coarse chipping for pelleting or particle board core
- Sawdust (6,7%) accounting for 972 Ton burned.
- Shaving (6,7%) accounting for 972 Ton devoted to pelleting.
- Sanding dust (2%) around 291 Ton devoted to pelleting.

Depending on the characteristics and properties of the raw materials they can be sent to different possible uses,

Table 4: Waste division detailing the different categories

Annual generation of the different by-products (Ton/year) Reference Dry plank			
SCRAPS	From trestles line	1.555 Ton (10,7%)	1.944 Ton (13,4 %)
	From furniture line 1	194 Ton (1,35%)	
	From furniture line 2	194 Ton (1,35%)	
SAWDUST	972 Ton (6,7%)		
SHAVING	972 Ton (6,7%)		
SANDING DUST	291 Ton (2%)		
BARK	3.042 Ton (9 %)		
TOTAL	7.221 Ton		

The basic characterization of the by-products is stated in the following table:

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Table 5: Characterization of by-products

	Bark	**Shavings, saw dust and sanding dust**	**Furniture scraps**		**Trestle scraps**
			Furniture 1. Plank	*Furniture 2. Boards*	
Moisture (%)	50	9,5-13,5	11,8	14,2	9,5
Length (cm) variations	0,3-1,5	-	21-30	4,5-10	3,9-32
Width (mm)	30-100	-	70	250	40
Thickness (mm)	10-40	-	15	20	17

<u>Moisture content</u>: affects the shrinkage and swelling behaviour of wood. A high humidity content in wood may lead to a retraction in dimensions at a low humidity ambient, so changes in the dimensions can be notorious and cause detachment of pieces, fences etc. On the other hand, an initial low humidity percent can cause swelling and internal forces play and important role in creating defects, but when considering particles for boards production humidity is a parameter controlled mandatory in the process. So, the initial values could vary in a great extent. However, the moisture ranges are very small.

The different approaches chosen for the treatment of by-products are presented below according to the different by-products. The different by-products can be upgraded in particle boards or fibre based boards (specially in medium density fibre board or in insulation panels). Considering the different wood by-products;

- Shavings and sawdust, generated in the cutting process, could be used directly as raw materials for particle board production. Sanding dust, in a certain extent, as fines.
- The fractions that need a treatment to produce boards are bark and scraps
    - Bark is treated in a knife cutter machine and after a post treatment in a milling machine to arrive to bark powder (Possible use as HCHO scavenger additive for particle board production).
    - Scraps are treated in a drum chipper and milled in a flaker mill. Also, a possible intermediate step in a knife cutter can be necessary for all the chips no complying with the maximum length allowed in the flaker,

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Figure 2: By-products treatments and final use in particle boards

2.2.1. Scraps

Wooden scraps come from the cutting of planks. They represent the biggest quantity on all ASTI´s production lines. Nowadays, scraps are reduced to obtain chips for pellets and wooden boards fabrication (external).

A selection of these pieces with the appropriate size and characteristics will allow to use them in high value options. specifically, the work has been focused on retaining value of those pieces, utilizing them for manufacturing of mosaics, self-supporting surfaces for furniture applications.

Moreover, the high quantity of virgin wood present also allows the production of high-quality fibres.

The 3 different types of scraps (2 from the 2 different furniture lines and one coming from the trestle line) have 2 fixed dimensions in almost all the pieces and variations are present only in the length. Control of the scrap's generation has arrived to three different length distributions:

- Pieces coming from the mechanization of trestles, A follow up of them in a monthly working basis has identified that they represent the 80% by weight of the total amount of scraps.

  Dimensions followed up by the company are in the ranges:
  - 3,9< Length < 32
  - Width= 40
  - Thickness =17
- Pieces coming from the fabrication of furniture. A follow up of them in a monthly working basis has identified that they represent the 20% by weight of the total amount of scraps. These pieces are all of them rounded-

  Furniture line 1: Dimensions followed up by the company are in the ranges:
  - 210< Length < 300
  - Width= 70
  - Thickness =15

  Furniture line 2. Dimensions followed up by the company are in the ranges:
  - 45< Length < 100
  - Width= 250
  - Thickness =20

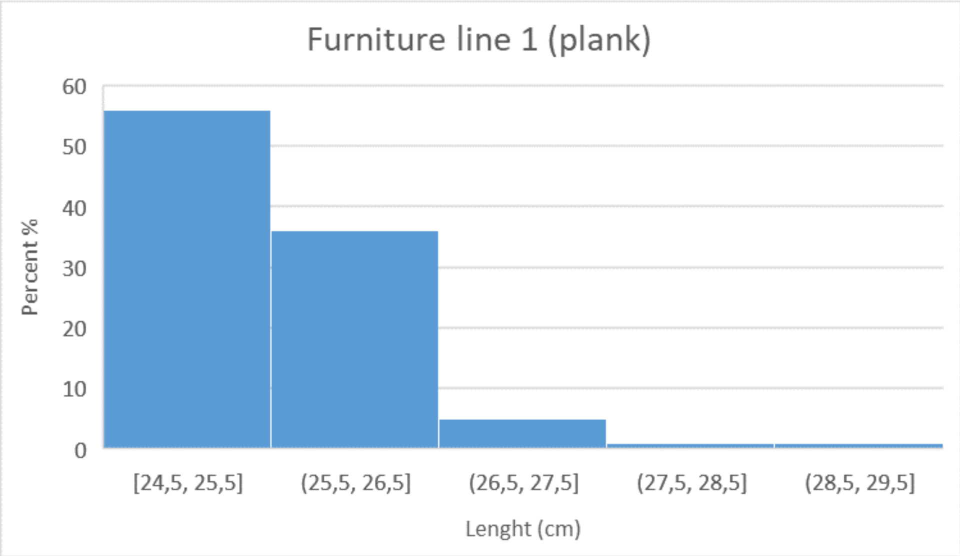

Figure 3: Length variability of Furniture line 1 (plank) scraps

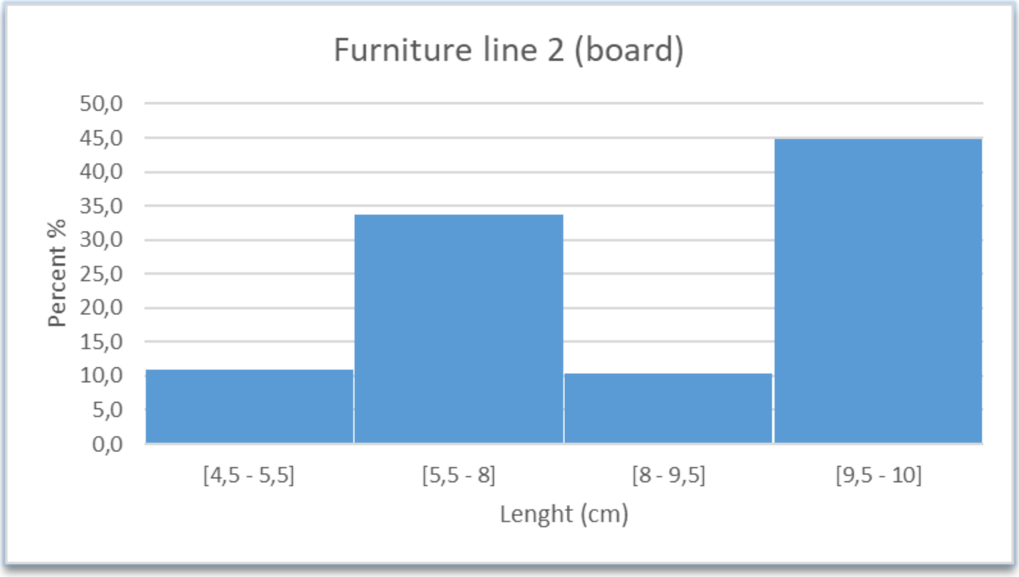

Figure 4: Length variability of Furniture line 2 (board) scraps

Figure 5: Length variability of trestle scraps

The different scraps options are mechanically processed in order to arrive first to high quality chips and thereinafter to produce high quality fibres, able to substitute those used in the manufacturing of fibre panels (specially Medium-density or High-density fibre boards) and insulation wooden panels (low density, being the rest used in wooden chips production

Once the fibres are obtained, the different products will be prepared in WP6

Table 6: Definition of different fibre boards related to density

Board	Density Kg/m^3
HDF (High density fibre board)	800-1.000
MDF (Medium density fibre board)	650-800
LDF (Low density fibre board) or insulation board	<650

CHIPPING EXPERIMENTS

The different experiments in the chipping machine to arrive to standardized dimensions have considered different process parameters. The quality of wood chips is very influenced by the chipping process conditions, such as the speed of the line and the speed of the rotor, the kind of sample or even the moisture content of the raw material.

The analysis of the dimensions revealing the different dimensions after the chipping process is made sieving the particles.

Depending on the obtained dimensions, especially the length, chips are adequate for a further processing into fibres or the material or can be sent to trials for producing Particle Boards.

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► Influence of the line speed

Pilot scale chipper trials have been carried out keeping all parameters fixed except speed, Subsequently, tests have been repeated by varying the velocities again and introducing variables such as material type and moisture content of the samples.

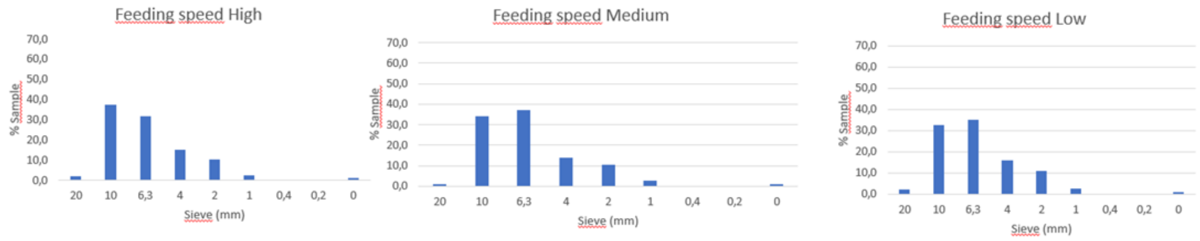

Figure 6: Influence of feeding speed in the particles length. Trestle samples

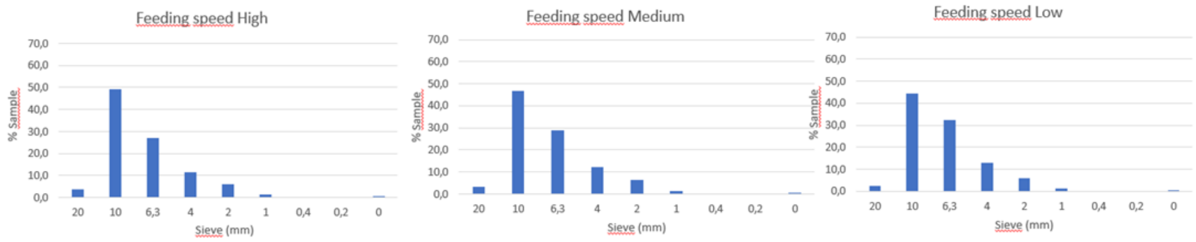

Figure 7: Influence of feeding speed in the particles length , Wet trestle samples

Controlling the rotor cutting speed at a medium value

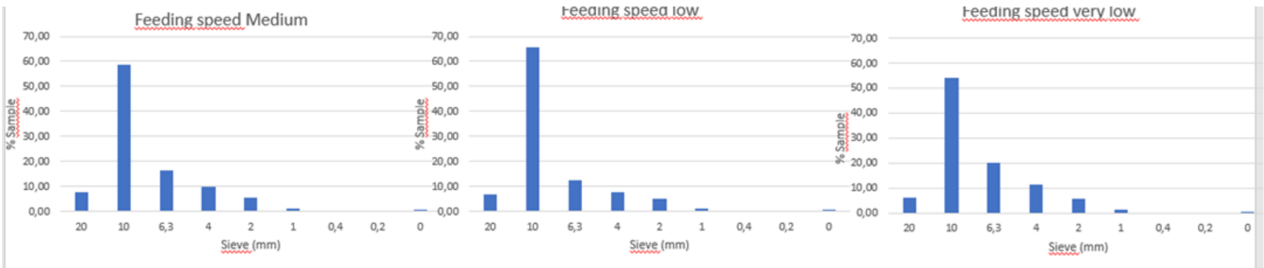

Figure 8: Influence of feeding speed in the particles length , Furniture line 1 (plank) samples

Only slight differences can be seen depending on the speed of the feeding line. Higher the feeding speed, little bit higher the length of the chips.

In general, higher the feeding speed, higher the percent of bigger particles, but not a remarkable influence parameter.

Figure 9: Samples of highest length at different feeding speeds

► Influence of the humidity of scraps

Pilot scale chipper trials are considered comparing dry and wet samples. Evaluation made at different feeding speeds. Experiments have considered different scrap origins.

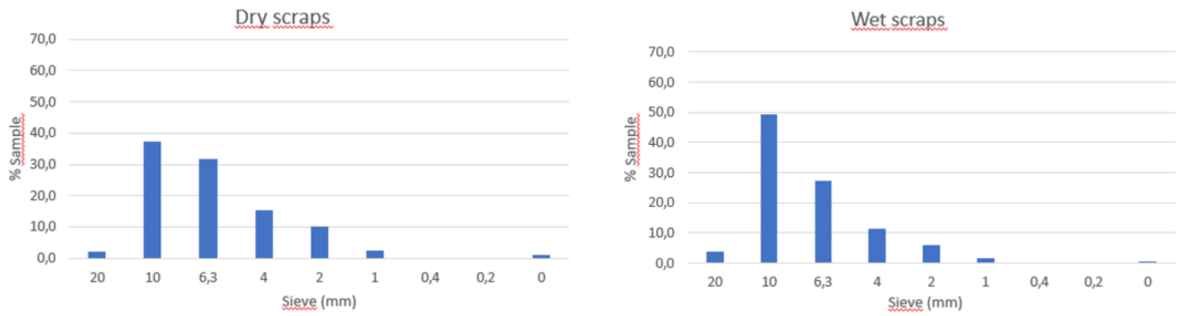

Figure 10: Influence of the samples humidity in the particles length , (High feeding speed; Trestle samples)

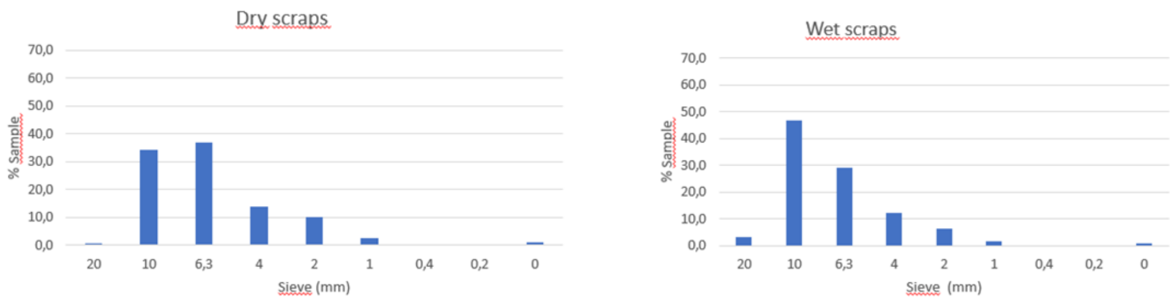

Figure 11: Influence of the samples humidity in the particles length , (Medium feeding speed; Trestle samples)

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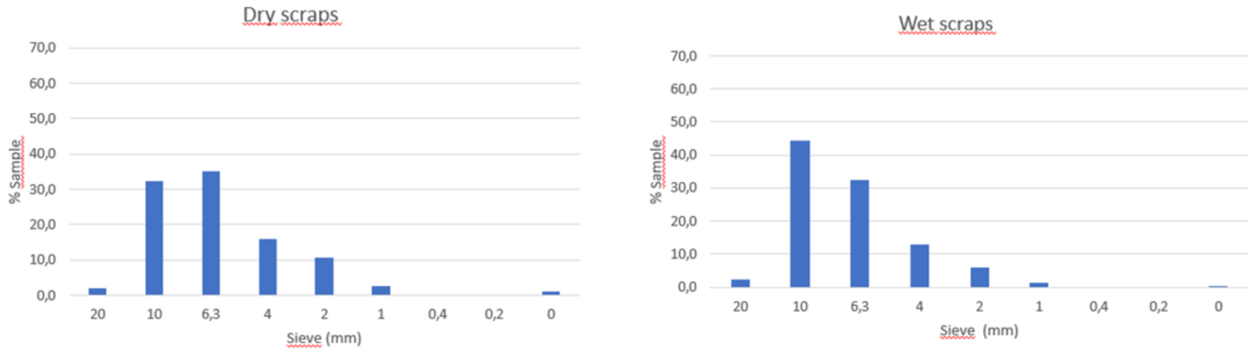

Figure 12: Influence of the samples humidity in the particles length , (Low feeding speed; Trestle samples)

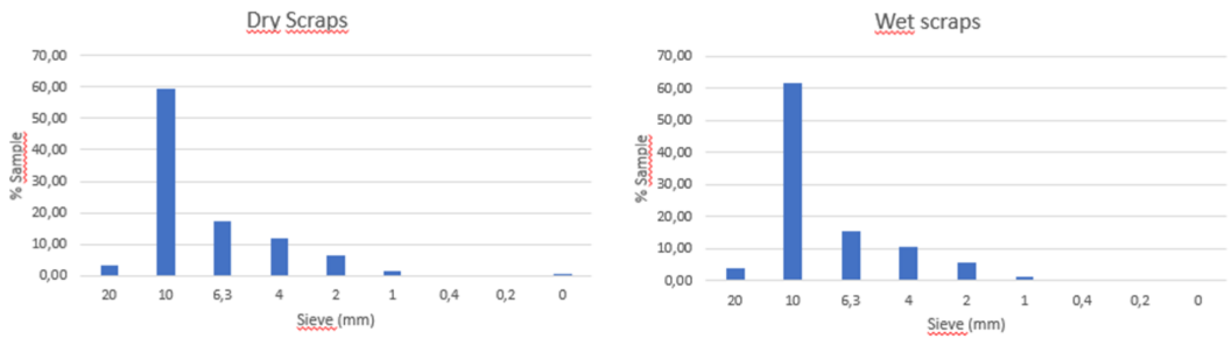

Figure 13: Influence of the samples humidity in the particles length , (High feeding speed; Furniture line 2, board samples;)

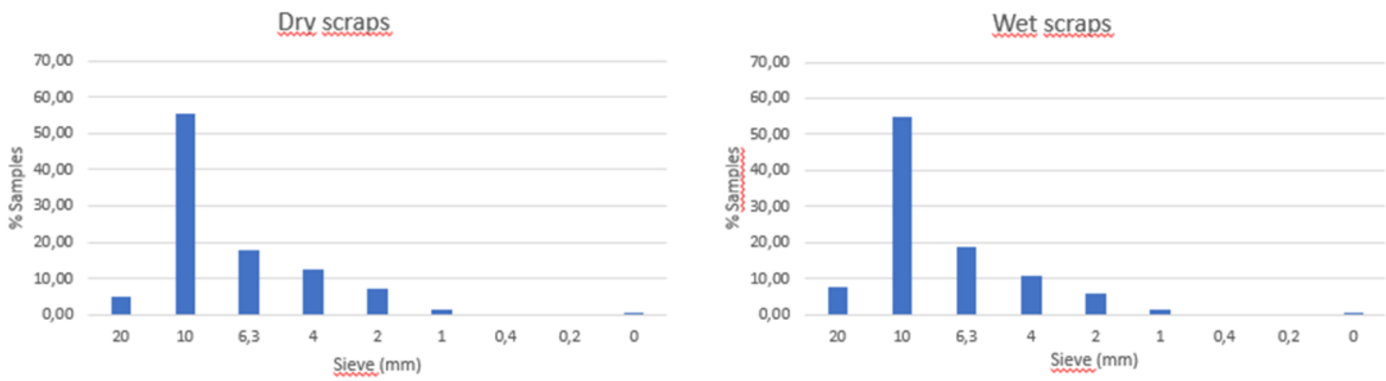

Figure 14: Influence of the samples humidity in the particles length , (Low feeding speed; Furniture line 2, board samples;)

In all cases, it can be stated that wet scraps give higher percent of long chips in trestle scraps. The same tendency but less remarkable in other scrap types.

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► Influence of the rotor cutting speed

Evaluation made at different rotor (with knives) speed. Experiments have considered different scrap origins.

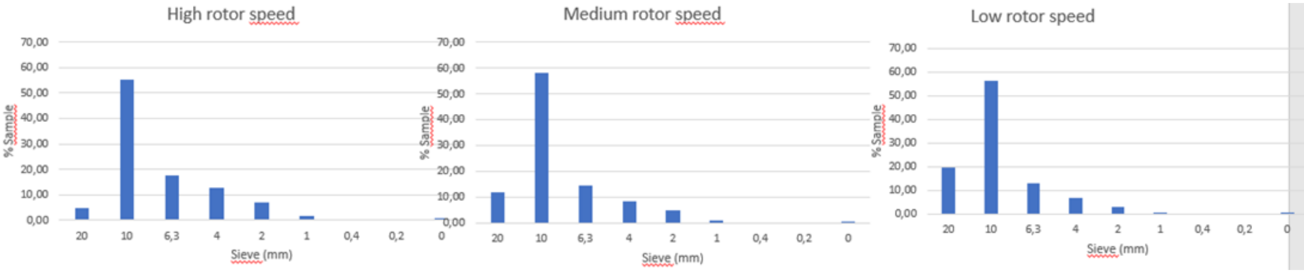

Figure 15: Influence of the cuting rotor speed in the particles length , (Low feeding speed; Furniture line 2, board samples;)

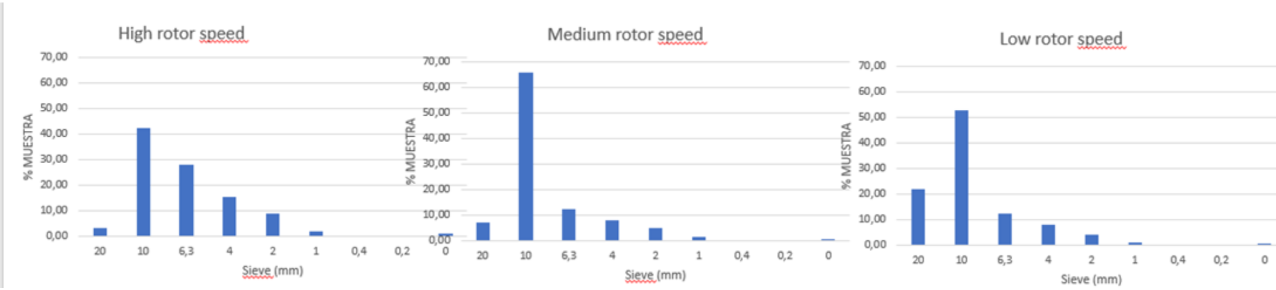

Figure 16: Influence of the cuting rotor speed in the particles length , (Low feeding speed; Furniture line1, plank samples;)

Lower the rotor speed, higher the percent of highest particles.

Figure 17: Visible differences between highest samples with low rotor speed (left) and medium rotor speed (right)

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► Influence of type pf sample

Considering the 3 scrap types.

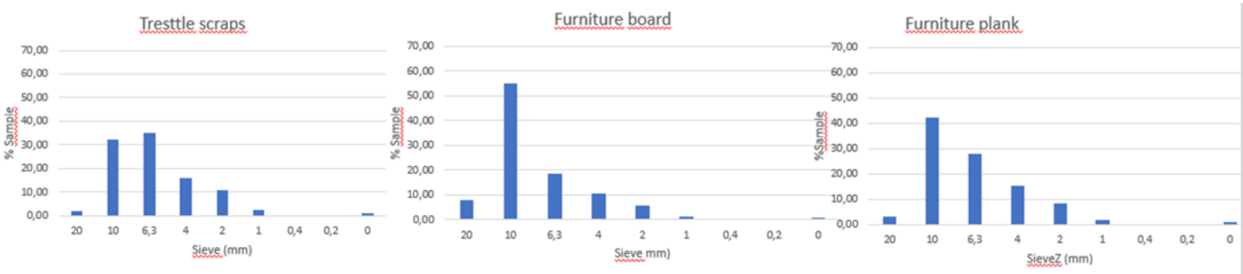

Figure 18: Influence of the type of scrap sample in the particles length, (Low feeding speed; high rotor speed)

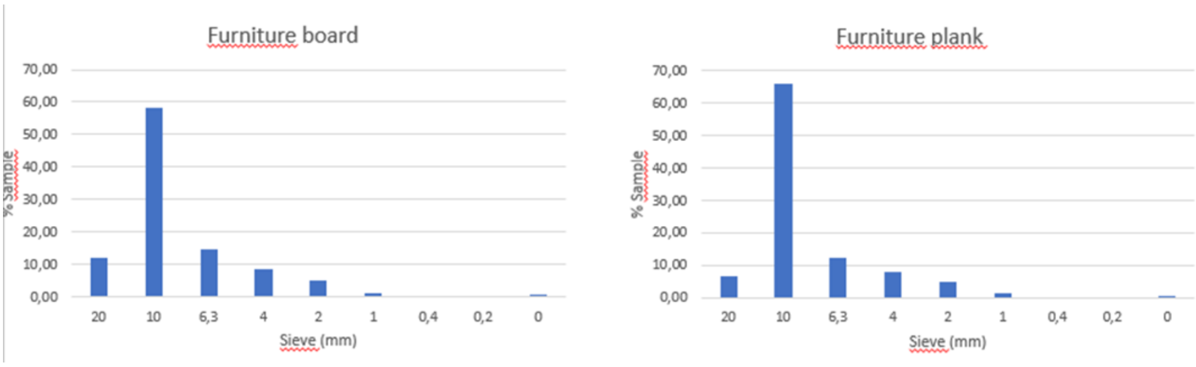

Figure 19: Influence of the type of scrap sample in the particles length , (Low feeding speed; high rotor speed)

Figure 20: Influence of the type of scrap sample in the particles length , (Low feeding speed; medium rotor speed)

Dimensions also depend on the type of by-product.

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►Milling process of high length particles

The particles not dedicated to refining (fibres) are introduced in a milling process to obtain core particles for particle boards.

Figure 21: Processing of chips to arrive tgo imlled particles in Pallman milling

Figure 22: Aspect of the different fractions after sieving

REFINING STEP

Refining process is the following step for the highest chips obtained in the previous chipping process.

Experiments are made jn a Refiner (Andritz AG,), termomechanical pulping pressurized discontinuous refining.

The chips are squeezed, compressed and heated with steam under pressure and high temperature to obtain the defibration of the chips.

Slight differences in some of the refining parameters make the difference in the final fibre properties. The objective is to arrive to high quality fibres able to be used in fibre panels and insulation, depending on the final characteristics (the highest quality is sent to panels production of higher mechanical properties required).

Experiments are being considered with some constant parameters which are less relevant in the process.

- Rotation speed fixed at around 2.900 rpm
- Pressure between 5-7,5 bar. Parameter linked to the temperature needed for the thermomechanical process (always above 150ºC)

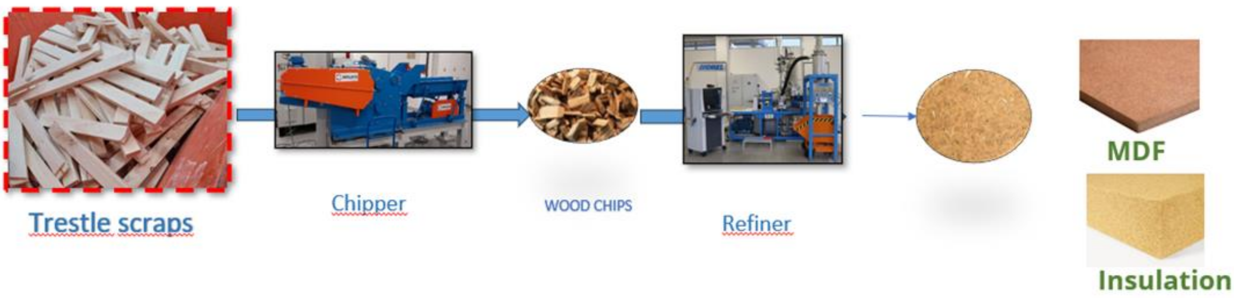

Figure 23: By-products treatments and final use in fibre boards

The variables taken into account are the disc gap and the retention time.

The control of the obtained fibres is made in a VALMET Fiber Image Analyzer FS5, measuring the medium length (mm) and the within microns.

Both fractions will be considered apart in the experimental design to make the correlation with final properties, not only considering different percents of the different materials, but also the ratio between core layer and external layers, and also the size of the chips.

2.2.2. Bark

The debarking is related to the wood specie, not being necessary for certain species such as beech or poplar but being necessary for pine.

Radiata pine bark is removed from logs and usually is used for mulching. Bark in wooden boards production is generally unwanted. However, it can be introduced in a certain extent for particleboard production, after appropriate mechanical treatment and sizing by milling.

There are scientific references paying attention to the possible uses of bark as formaldehyde scavenger in the production and use of particle boards[1] . DIGINTRACE considers introducing fractions of bark, pretreated in particle boards as formaldehyde scavenger.

It has been concluded that a new stabilisation step is necessary to arrive to moisture contents of 10%. So, the particles could reach better the same moisture degrees presented by the chips for particle board production.

The necessary mechanical treatment is designed to arrive to particle sizes able to be introduced in a certain percent in the outer layer particle boar section and normally present in the fabrication of particle boards.

The first sizing was made using a knife Cutter machine (Amis GSL18). This pretreatment is necessary to arrive to the minimum conditions to for particle to enter into the following size reducing step, followed by a finer reduction in a milling machine (Palman PXL18) . Bark powder was converted in different size fractions in a vibrating sieve shaker.

The different experiments in the milling machine to arrive to standardized dimensions included milling rotor speed and sieves:

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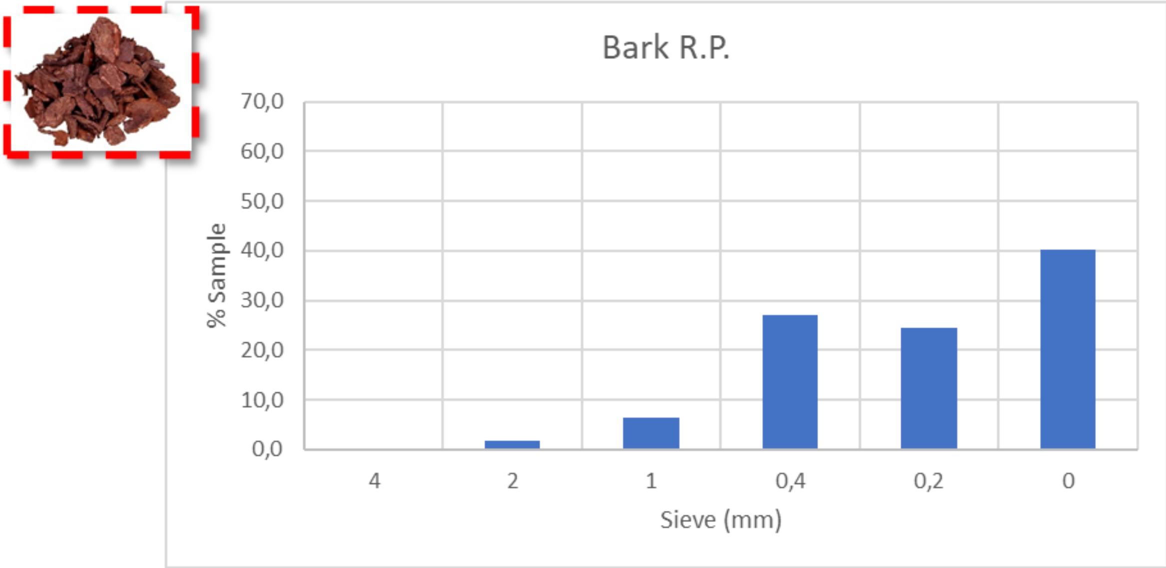

Figure 24: Radiata pine bark sieving after milling

Figure 25: Bark milled

The bark powder will be used, except the finest portion (under 0,2 microns). The obtained bark fines will be an option to be considered in task 6. 2- Systems design will use this fine grade of bark particles, considering that the small size connected to the highest surface area could be the opportunity to obtain higher formaldehyde scavenging in a small addition content, so not affecting mechanical parameters.

[1] Efficiency of bark reduction of formaldehyde emission from particle boards. Medded S , Gajser U. Wood Research 64(2): 2019

2.2.3. Shaving/Sawdust and sanding dust

Shavings and sawdust are directly generated in the fabrication process and are both options to be introduced in the experiment design to obtain particle boards. Different ratios will be used to correlate the improvement or decrease of mechanical properties. Their influence in the final properties of Particle boards will be studied.

Properties of wooden based panels are very related to the dimensions of the particles and mechanical properties and fall dramatically when the dimensions are very small.

Sanding dust is categorized as fines, being the most of them under 200 microns, avoiding their use in the manufacturing of particle boards.These fines can be used as biobased filler in mastics to diminish the shrinkage and give a natural colour.

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2.3. By-products in MENEXES

CHIMAR collaborated closely with ICCS and MENEXES in WP5, to enhance the sustainability of particleboard manufacturing by effectively utilizing wood residues. CHIMAR communicated the specifications of the wood chips used for the production of particleboard to ICCS, who is responsible for the sorting mechanism, and to MENEXES, who supplies the wood residues and will manufacture furniture prototypes from the produced boards. MENEXES provided detailed information on the various types of wood-based panels they utilize in their manufacturing processes, and CHIMAR identified which types of panels would yield suitable chips to replace virgin wood chips in pilot particleboard panels. Subsequently, MENEXES sent wood residues from the chosen panel types to CHIMAR, where they were shredded into chips. These shredded chips were then sieved to select the desired fractions. The selected chip fractions from each panel type were then forwarded to ICCS, who began developing the sorting system to integrate these chips into the particleboard production process.

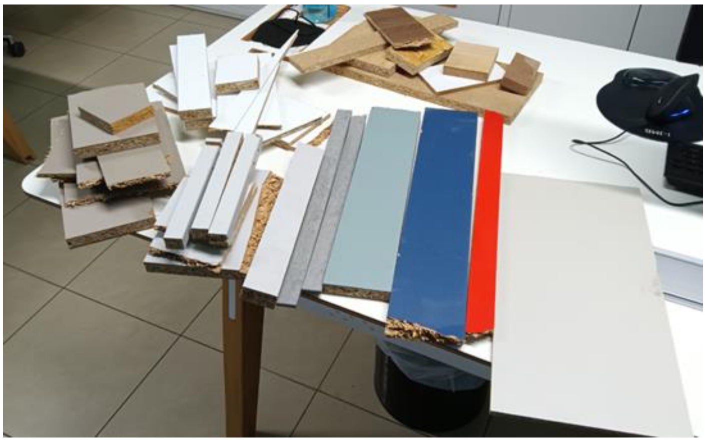

Figure 26: Underutilized wood residues from MENEXES

Figure 27: Shredded chips by CHIMAR ready for sorting

3. Machine vision-based wood re-design toolkit

Big and regular wasted wood scraps can be reused to create new and up-cycled by-products to avoid downgrading their properties. For that, automatization of workflows is essential, as reusing wasted scraps must be economically viable. In order to do that, sorting and selecting the valid scraps is a key step to automate as it would otherwise require vast amount of manual labour. Even after selecting the scraps that are going to be reused, the byproduct produced with these scraps must be as saleable as possible, and must be built automatically to reduce costs as much as possible, so the automatization of product construction is also a key step.

In order to make a valid automatized workflow to create a saleable byproduct using wood scraps, the idea in this deliverable is to present a method to automatically select which scraps are suited to be reused, catalogue their properties, create a generative design algorithm to create beautiful mosaics and automatize the building process of it using a robotic arm that, taking the output of the generative design algorithm, is going to be able to create the mosaic automatically, thus reducing the manual labour as much as possible.

3.1. Introduction

In order to create the mosaic, there are multiple steps that should be automatized (**Figure 28**). Initially, scraps that are going to be reused must be selected and catalogued, and the ones that are not going to be used must be discarded. After cataloguing the scraps with multiple properties, these scraps must be sorted in a way that can create a beautiful mosaic. For that, a generative design algorithm can be trained. This algorithm can create a mosaic based on multiple restrictions and scrap properties that enables to customize the output. At last, the generative design algorithm's output can be used as input for a robotic arm to automatize building of the mosaic.

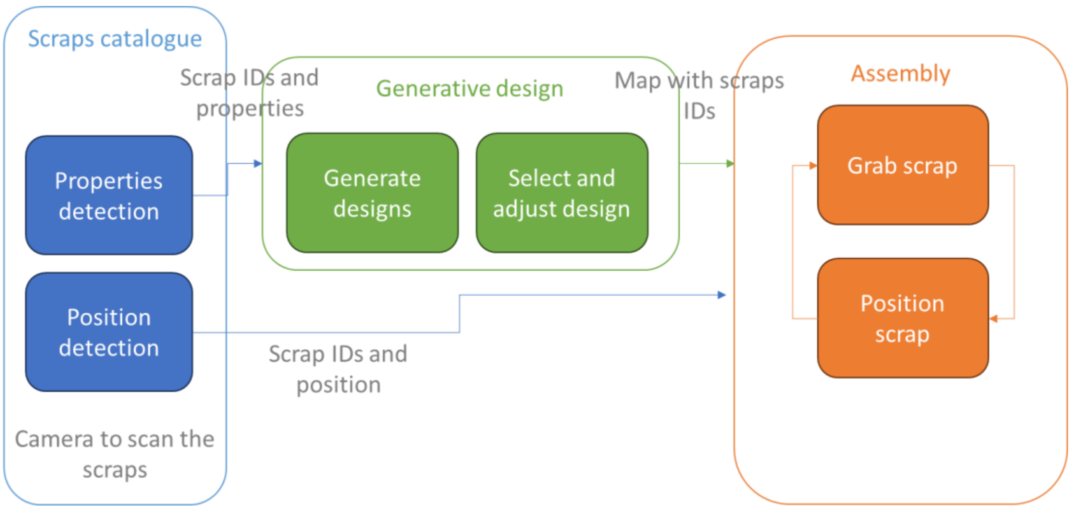

Figure 28: Process workflow

3.1.1. Vision-based scraps sorting and cataloguing algorithm

The first step to automatize the reuse of wood scraps is to select which scraps are usable and catalogue by their properties. This should be ideally done in real time, allowing the process to work as a production chain, in order to create as much mosaics as possible and to attach the process to already running production chains.

3.1.1.1 Visual Foundation models

In recent years, visual foundation models, such as YOLO (you only look once), have gained popularity in sorting and selecting task, outranking other visual computer-based methods. YOLO is an open-

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source algorithm that uses neural networks to detect objects in real time. It is trained to detect more than 9000 classes by default, and it can be trained to detect objects that are beyond its scope. It can be used for identification, selection or object and instance segmentation.

Figure 29: YOLO detection of multiple classes in real time

In more recent year, in 2023, META released their visual foundation model, SAM, a state of the art image segmentation model. Contrary to YOLO, SAM doesn’t classify objects, but it can segment anything in an image, thus the name SAM-Segment anything. This can be really helpful for automatizing the generation of datasets, since it can automatize the labelling of pieces of an image. Besides, it has some promptable capabilities, allowing to add some logic to what it is segmenting.

Figure 30: SAM segments the picture without knowing what it is segmenting

After releasing the SAM model, META-AI released DINOV2, a self-supervised vision transformer model that exceeds the state of the art of vison-based tasks in multiple tasks, such as depth estimation, feature learning and clustering and image segmentation. This model can be used to segment elements, and it can learn automatically to classify without human supervision, making it easier to use in comparison with YOLO, since it skips the training part needed in order to do the fine tuning.

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3.1.1.2 DINOV2 model development

Both YOLO and DINOV2 models can be used to make instance segmentation and fulfill the automatic detection of wood scraps in real time. However, DINOV2 has the advantage of been a self-supervised model, meaning that there is no pre-training needed that involves generating manually a labelled dataset of images. This can be a big difference since the cost of creating the algorithm drops drastically and it eases the repeatability for when more scraps or different properties are added. However, for both there is a previous work that needs to be done in order to 1) train the YOLO model for selecting wood scraps and 2) get the cut-outs of wood scraps in every photo to get individual wood scrap embeddings.

For this reason, DINOV2 is going to be used first to see the viability of the selection process, saving the YOLO process as a safeguard.

To create a selection model with DINOV2 several steps must be done:

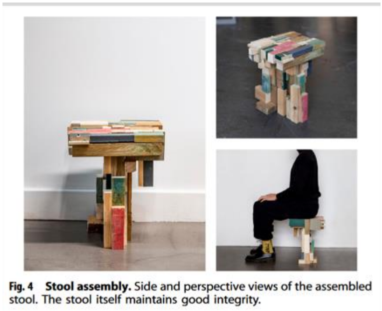
1. Get the cut-outs so DINOV2 could learn features of each wood scrap instead of the whole picture containing multiple scraps.
2. Get embeddings of each wood scrap from the cut-outs and make the clustering to detect which features are analyzing.
3. Use the embeddings to catalogue the cut outs into the desired properties that are going to be used by the generative design algorithm.

A risk using DINOV2 model could come when clustering the embeddings, since there is no guarantee that the clustered embeddings will match with the properties needed by the generative design algorithm.

3.1.2. Generative design of wood panel from scraps catalogue

The potential of computational design to facilitate the reuse of wood scraps has already explored in the literature (**Error! Reference source not found.**).

Table 7: Examples of computational design for wood scrape reuse

Framework for Sustainable Building Design and Construction Using Off-Cut Wood[8].	Robotic Fabrication Strategies for Spatial Reciprocal Structures from Plate-Shaped Wooden Production Waste[9].	A genetic algorithm is used to create a table from branches[10].

Generative design is a new paradigm which leverages computational algorithms and artificial intelligence to facilitate the exploration of a wide array of design possibilities and to propose fast initial designs based on a set of design goals and constraints. In the context of wood scrap up cycling, generative design has the potential to contribute to the maximization of the utilization of material resources, while fostering sustainable mass customisation of furniture and decorative by-products.

The method we propose is, using the specific characteristics of the available wood scraps categorised in the previous step, such as size and aesthetic, to generate a multitude of unique and feasible designs that can then be edited and customized before assembly. Because, together with the geometrical feasibility of the design, the aesthetic aspect is of upmost importance, the generative design algorithm will be trained based on human feedback on the initially generated designs. The algorithm will be prepared for periodical retraining based on sold design to account for the latest trend in the customer's taste.

There are several types of generative design methods. A distinction can be made between methodologies based on images, where the algorithm output is an image of the desired design (e.g. a floor plan for a new building), or based on graphs, where the output is a graph representation of the design (e.g. geometrical relation between the room of a floor plan). Graph-based methods requires more post-processing to display the design, but they allow better control on the design and direct exploitation. For these reasons, a graph representation of the design is selected for this project, where the graph nodes are the scraps, whose properties are the dimensions and aesthetic properties of the scrap and the edges the relative position between them.

First programmatically and manually generated designs will be created and submitted to human vote to serve as training data for the generative design process. This input data will then train a Graph Neural Network (GNN) generative model. This model will then be able to propose various design based on a more restricted scrap catalogue provide by the previous step. The design will be manually adjustable if desired and once the final design is selected for production, the graph will be covered in a list of coordinate for the robotic assembly.

3.1.3. Robotic system

The automatic robotic cell will participate in two of the phases of the wood scrap reutilization process, firstly it will position the camera to capture the images used by the recognition algorithm and secondly

[8] Yu, Boyuan, Jianing Luo, Yi Shi, Mingming Zhao, Adam Fingrut, and Lei Zhang. 2023. 'Framework for Sustainable Building Design and Construction Using Off-Cut Wood'. Npj Materials Sustainability 1 (1): 1–11. https://doi.org/10.1038/s44296-023-00002-8.

[9] Augustynowicz, Edyta, and Nikita Aigner. 2023. 'Building from Scrap: Computational Design and Robotic Fabrication Strategies for Spatial Reciprocal Structures from Plate-Shaped Wooden Production Waste'. *Journal of Architectural Sciences and Applications* 8 (1): 38–53. https://doi.org/10.30785/mbud.1244395.

[10] Zirek, Seda. 2023. 'Bottom-up Generative up-Cycling: A Part Based Design Study with Genetic Algorithms'. Results in Engineering 18 (June): 101099. https://doi.org/10.1016/j.rineng.2023.101099.

after the generative algorithm has created the mosaic design to pick the scraps and position them in the designated position to build up the mosaic board.

The robot cell will use a personalised end-effector that composes the camera needed for capturing the images for the recognition algorithm and a vacuum gripper to pick and place the wood scraps from the input trays to the position decided by the generative algorithm to build up the mosaic board on the output tray.

Figure 31. Vacuum gripper and camera.

In the first step, the robot will automatically position the camera in a consistent and known position for each of the input trays and capture the images needed for the recognition algorithm to detect, log, categorize and measure the different wood scraps. Once the recognition algorithm detects all the scraps it will feed the size and features to the generative algorithm, but also will send the position and orientation of each of the scraps on the input trays. This information will later be used to automatically generate the trajectories for the pick and place tasks.

In the second step, system will be fed by the generative algorithm with the position of the different wood scraps used in the mosaic board. This information together with the position of the scraps on the input trays will be used by the system to automatically generate the trajectories and commands necessaries to pick the selected scraps form their position on the input trays and place them in their position on the mosaic board, on the output tray. The system will generate both the trajectories and the commands for the vacuum system required to correctly both pick and place the wood scraps.

3.2. Implementation

To facilitate the process of digitisation and cataloguing of wood scraps, a compact laboratory has been erected. This space is specifically designed for the correct identification and classification of the various wood samples.

In this laboratory, the height and position from which the assembly robot would visualise the samples have been simulated. This simulation process is crucial for the training of the cataloguing models, as the training must be with the same type of images (distance, position, size, etc.) that the images that the robot would capture during the mosaic board assembly process. In addition, these images, after cataloguing them, are also used in the generative design described above.

Therefore, this laboratory not only serves as a space for the digitisation and cataloguing of wood samples, but also plays a vital role in the preparation and training of the robot for the assembly of the mosaic board.

3.2.1. Scrap labelling

To carry out an effective cataloguing of the woods, it is of utmost importance to define the characteristics that are relevant to the final objective. This process of definition is not arbitrary but is intrinsically linked to the purpose and functionality of the final product. The final designs of the boards are intended to be decorative, which implies that the aesthetic characteristics of the woods are of relevance. However, aesthetics is not a one-dimensional concept, but can be influenced by a variety of factors, including colour, texture, grain, and shape of the wood.

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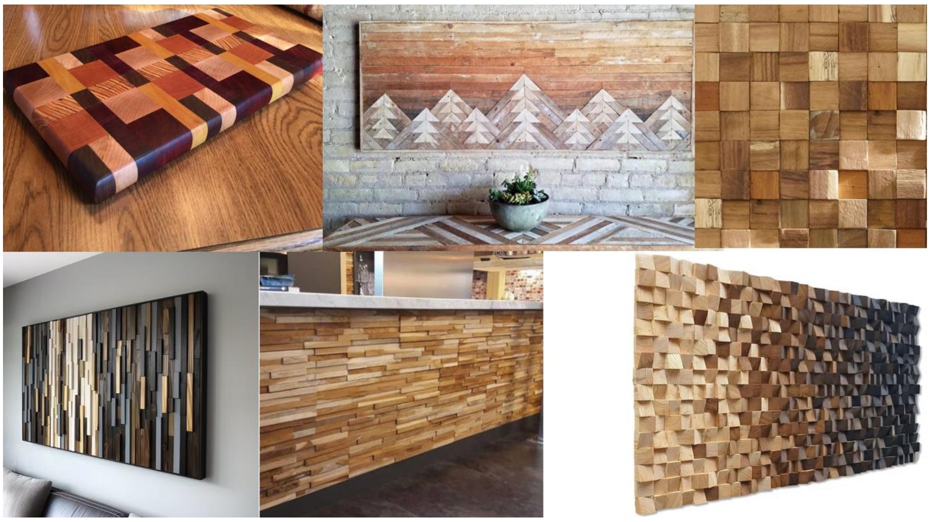

Figure 312: Inspiration boards

The initial phase of cataloguing the wood samples was carried out manually, analysing a total of 69 samples.

Following the inspiration and objectives that are sought to be achieved with the mosaic boards, a comprehensive visual review of the wood scrap samples was conducted. This process not only involved an evaluation of the physical characteristics of the samples, but also a consideration of how these characteristics could contribute to the aesthetic and functional objective of the mosaic board. These characteristics not only serve as classification criteria for the wood samples but will also be considered in the generative design process, allowing the creation of mosaic boards that are both functionally solid and aesthetically pleasing.

As a result of this review, it was decided to identify a series of key characteristics in the wood samples. These characteristics were selected for their relevance to the design and functionality of the mosaic board, as well as for their ability to differentiate between the various scrap samples by grouping them according to the identified characteristics.:

- Eye/No eye
- Drawing: lines, veins
- Colour: greenish, light, dark
- Ends: straight, skewed
- Size measured for boundary approximation (height, width, depth)

Figure 33: Manualy analysed wood scrap

	Alto	ancho	fondo	ojo	dibujo	color	esquinas
1	28	5	2,2	no	lineas	verdoso	plana
2	25,8	4,8	2	no	lineas	verdoso	plana
3	29,5	5	2,2	no	lineas	claro	plana
4	29	5	1,6	medio	lineas	verdoso	plana
5	29,2	5	2,3	no	lineas	claro	plana
6	28,8	5	2,2	lateral	lineas	claro	plana
7	29,6	5	1,7	medio	vetas	oscuro	plana
8	29,5	4,8	2	no	vetas	verdoso	plana
9	29,5	5	2,2	lateral	vetas	claro	plana
10	29,2	5	1,8	no	lineas	claro	plana
11	29,7	5	2,3	no	vetas	verdoso	plana
12	29,2	5	2,2	no	lineas	claro	plana
13	29,2	5	1,2	no	lineas	claro	plana
14	30	5	2,2	lateral	vetas	claro	plana
15	31	5	2,2	medio	vetas	claro	punta
16	30,2	5	2,2	medio	vetas	claro	plana

Figure34: Table of results of manual wood scrap cataloging

In the second phase of our wood cataloguing project, we have established a small laboratory that simulates the position and focus that the assembly robot will have. In the laboratory, we have installed the 4K 2160P IMX317 Sensor Camera, the same one that will be used by the robot in the mosaic board assembly process. Also, this space is illuminated by a specific light source to ensure the quality and consistency of the captured images.

We have designed a specific space for capturing images of wood, with dimensions of 0,755 x 0,905 meter board and 1,35 meters from camera to scraps.

Figure 35-36: Wood scrap sample capturing space, simulating the characteristics of the assembly robot

In this controlled environment, we have captured images of bit more than 1,000 wood samples. These samples were grouped into batches of about 25 elements each. On the one hand, to avoid overload the capture space and preventing occlusions, and on the other hand, to facilitate the handling and processing of data.

From this set of samples, we have obtained a total of 86 images (taking images of both sides of each scrap) that have been processed and classified using the DINOV2 and SAM algorithms. This process is described in the following point of the deliverable.

Finally, with the automatic results obtained from this process described in the following point of the deliverable, our goal is to find associations between these groupings and the characteristics that were manually identified in the first phase of the project. This correlation will allow us to improve the precision and efficiency of our wood cataloguing system.

3.2.2. DINOV2 vision-based wood scrap cataloging

One of the features of DINOV2 self-supervised model is to make instance segmentation. In this case, for the model to learn what is segmenting, it will be trained with pictures of wood scraps that will be translated to embeddings. This will allow us to detect scraps in real time and get classify them by properties.

To be able to launch DINOV2 easily, a docker file has been created that, since it can't be used on windows architectures:

1. Uses python image as base image
2. Installs git
3. Downloads DINOV2 model from the public github repositoy
4. Installs its requirements
5. Modifies some files in order to make embeddings

```
docker_files > Dockerfile > ...
# Use the official Python image as the base. DO NOT USE AN ALPINE IMAGE
FROM python:3.10.14-bookworm

# Install Git
RUN apt-get update && apt-get install -y git

# Set the working directory
WORKDIR /app

# Clone the DINOV2 repository
RUN git clone https://github.com/facebookresearch/dinov2.git dino

# set as module creating an empty __init__.py file
RUN touch /app/dino/__init__.py

# install requirements
RUN pip install -r /app/dino/requirements-extras.txt

COPY requirements.txt /app/requirements_proj.txt
RUN pip install -r requirements_proj.txt

COPY docker_files/vision_transformer.py /app/dino/dinov2/models/vision_transformer.py
```

```
docker-compose.yml
name: python_dinov2
services:
  dino:
    container_name: dinov2
    build:
      context: .
      dockerfile: ./docker_files/Dockerfile
    volumes:
      - ./src:/app/src
      - ./images:/images
      - ./output:/output
    #avoid closing the container
    command: tail -F anything
```

Figure37: DINOV2 Docker file & docker-compose file to be able to use it on windows architectures

This docker file, along with a docker compose file allows to launch any model of DINOV2 against the pictures that need to be analyzed, since, apart from loading the DINOV2 model in a Linux architecture ready to be used, it also loads in the container both the images, the output folder and the code to be executed.

Once the architecture is ready, our first step has been to create a method to extract all the embeddings from an image. For that, an extractor class has been generated that:

1. Opens the image
2. Makes size and normalization operations on it
3. Use the dinov2_vits14 model to extract the features.
4. Draw a plot converting the features to an RGB 128x128 image using principal component analysis PCA

This has led us to validate the feature extractor feature of DINOV2 using the 86 images of wood scraps

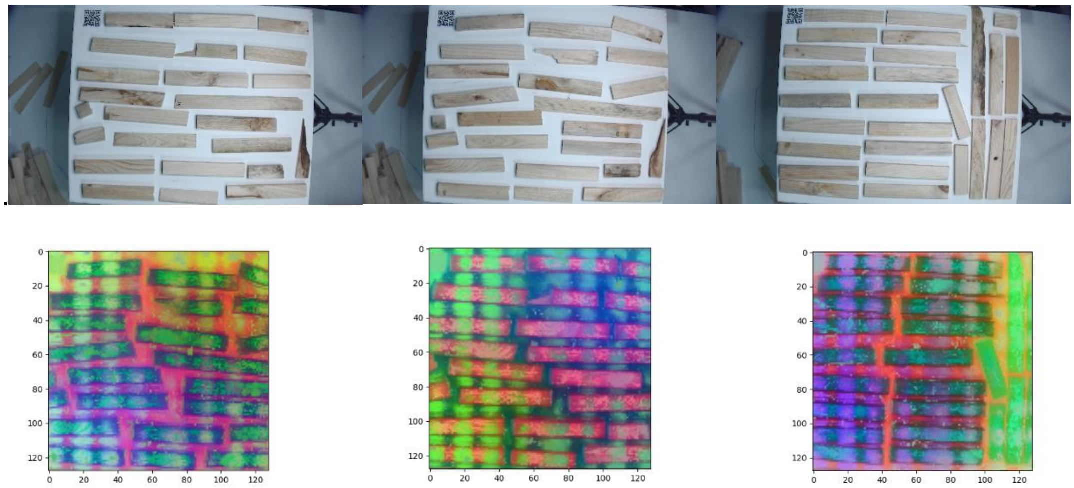

Figure38: DINOV2 feature extraction result

3.2.3. Wood scrap catalogue format

For an agile process, json files were selected as support for the scrap catalogue. Based on the characteristics defined above, the format of the scrap catalogue is the once illustrated in **Figure 1**.

```
{
  "scraps":[
    {
      "id": "0001",
      "size": [500,1000,2500],
      "eye": "no",
      "drawing": "lines",
      "color": "light",
      "end": "straight"
    },
    {
      "id": "0002",
      "size": [500,1000,3500],
      "eye": "middle",
      "drawing": "veins",
      "color": "light",
      "end": "straight"
    }
  ]
}
```

Figure 39: Scrap catalogue format

Table 8 defines the values of the different field.

Table 8: Scrap catalogue fields definition

Field	Values
Id	The reference number of the scrap.
Size	Height, width, depth in mm
Eye	"no", "middle", "side"
Drawing	"lines", "veins"
Color	"green", "light", "dark"
End	"straight", "skewed"

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4. Novel sensing and sorting techniques

In the DigInTraCE project, novel sensing and sorting techniques play a pivotal role in the wood valorisation process. These techniques are designed to enhance the purity and quality of wood chips, thereby producing high-value products like particleboards and MDF boards. The advanced sorting mechanisms are engineered to identify and eliminate impurities from wood waste with high precision and efficiency, using state-of-the-art technologies such as machine vision and robotic systems. This approach aligns with the project's broader objectives of advancing waste sorting and valorisation while adhering to sustainable practices.

4.1. Design of the Wood Sorter

The mechanical design of the wood sorter within the DigInTraCE project is integral to achieving high accuracy in sorting wood chips. This system incorporates several key components that work together seamlessly to handle various sizes and types of wood chips. The primary mechanical components include:

- **Drum Screener**: This device sorts wood chips based on size. The rotating cylindrical drum is equipped with multiple perforations corresponding to different size fractions (1-2mm, 2-4mm, 4-10mm, 10-20mm, 20-25mm). As wood chips pass through the drum, they are sifted into predefined categories, ensuring accurate size-based sorting.
- **Pneumatic Air Nozzles**: Positioned along the conveyor belt, these nozzles play a critical role in removing contaminants and impurities from the wood chips. The nozzles are controlled by a precise pneumatic system that targets and ejects defective wood chips, such as colored coated chips and oversized particles, ensuring that only high-quality material continues in the processing line.

The sensor system is a vital component of the wood sorter, designed to detect impurities and contaminants that impact the quality of the final products. The system integrates several advanced sensors:

- **RGB Cameras**: These cameras capture high-resolution images of the wood chips, providing detailed visual information about their surface characteristics. They are crucial for identifying visible impurities such as coatings and paint layers.
- **Hyperspectral Imaging (HSI) Cameras**: These cameras capture data across a wide range of wavelengths, enabling the detection of subtle differences in material composition and surface properties. The combination of RGB and HSI technologies ensures a thorough assessment of wood chip quality.

The data collected by these sensors are processed using advanced machine learning algorithms, classifying the wood chips based on their purity. This automated classification ensures consistent quality control throughout the sorting process.

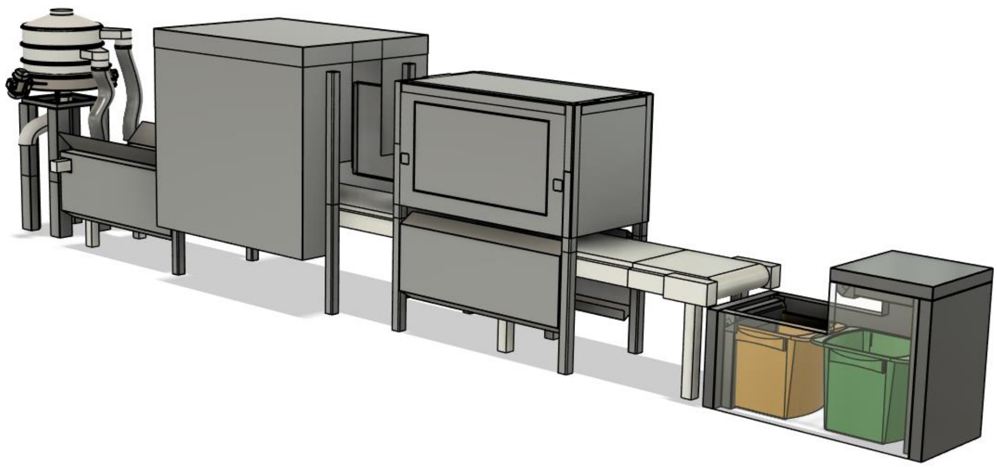

Figure 40: Wood sorter design

4.2. Algorithms and Processing Techniques

The core of the wood sorter's intelligence lies in its advanced algorithms and processing techniques. These elements work collaboratively to ensure precise sorting by analyzing data from various sensors and making real-time decisions. The system employs advanced image processing algorithms to analyze data from the RGB and hyperspectral cameras, performing several critical tasks to ensure the integrity and quality of the data before it is fed into the machine learning models. Initial image enhancement techniques improve the quality of raw images through noise reduction, contrast adjustment, and normalization of lighting conditions, ensuring that subsequent analyses are accurate.

Using the Segment Anything Model (SAM), the enhanced images are divided into segments to isolate areas of interest such as potential contaminants. This segmentation is vital for identifying impurities with high precision. Both RGB and hyperspectral images undergo feature extraction processes where key characteristics such as texture, color gradients, and spectral signatures are identified. These extracted features are then classified by custom convolutional neural networks (CNNs), which use cross-model attention mechanisms to combine information from hyperspectral and RGB modules. This integration ensures that subtle spectral features and visible characteristics are jointly considered, enhancing the overall classification accuracy of the system. More specifically, the sorting system is defined by fine-tuned machine learning models, including YOLO v8, the Segment Anything Model (SAM), and custom CNNs with cross-model attention mechanisms. These models are meticulously trained on extensive datasets to recognize patterns and classify wood chips based on their purity and quality.

- **YOLO v8**: Employed for its superior object detection capabilities, YOLO v8 identifies impurities and contaminants with high accuracy by processing input data from both RGB and hyperspectral sensors to pinpoint defects.
- **Segment Anything Model**: Excels at dividing images into meaningful segments, isolating areas of interest for focused analysis and precise impurity detection.
- **Custom CNNs with Cross-Model Attention Mechanisms**: Combine and enhance information from hyperspectral and RGB modules, improving the classification accuracy by jointly considering subtle spectral features and visible characteristics. The innovation lies on the use of latent features from both modules, and with the aid of Transformers-based, cross-modal fusion, important features are extracted for better accuracy.

These models continuously adapt to new types of impurities and improve their accuracy over time through ongoing training with new data. The combined outputs from these models provide real-time decisions to the control system, determining whether to accept or reject each wood chip based on its detected quality.

4.3. Impurity Separation and Impact

The implementation of pneumatic air nozzles is a cornerstone of the wood sorting system within the DigInTraCE project, designed to ensure the removal of impurities with unparalleled precision. This advanced technology targets and ejects defective wood chips, thereby enhancing the quality of the final product. The primary functions of these air nozzles include the separation of color-coated wood chips and oversized particles from the processing stream.

Figure 41: The air nozzles in the system

Functionality of Pneumatic Air Nozzles

Pneumatic air nozzles are strategically positioned along the conveyor belt within the wood sorting system. Their precise control mechanism allows for targeted removal of impurities based on real-time data provided by the integrated sensor system. The air nozzles operate as follows:

- **Detection and Ejection**: As wood chips move along the conveyor belt, RGB and hyperspectral cameras capture detailed images and spectral data. The deep learning algorithms, described earlier, analyze this data to identify impurities such as color-coated wood chips or particles larger than the predefined size fractions. Upon detection, the system sends signals to the appropriate pneumatic air nozzles to eject these impurities from the processing line.

- **Color-Coated Wood Chips**: Wood chips with coatings or paint layers present significant challenges in the valorization process. The RGB cameras, alongside the hyperspectal cameras detect these visible impurities. When an impurity is identified, the pneumatic air nozzles precisely target and remove the color-coated chips, ensuring that only uncontaminated wood proceeds further.

- **Oversized Particles**: Maintaining a consistent size fraction of wood chips is crucial for downstream processing. The drum screener initially sorts wood chips into specific size categories, but oversized particles can occasionally slip through. The pneumatic air nozzles are calibrated to identify and eject these larger pieces, preventing them from contaminating the batch and ensuring uniformity in the feedstock.

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Advantages of Using Pneumatic Air Nozzles

The integration of pneumatic air nozzles in the wood sorting system offers several advantages:

- **High Precision**: The air nozzles provide pinpoint accuracy in targeting and removing impurities, significantly improving the overall quality of the wood chips.
- **Efficiency**: By operating in real-time, the air nozzles ensure that impurities are removed instantaneously, minimizing downtime and maintaining a continuous sorting process.
- **Versatility**: The system can adapt to different types of impurities, whether they are color-coated wood chips or oversized particles, enhancing the flexibility and effectiveness of the sorting mechanism.
- **Quality Control**: The use of pneumatic air nozzles ensures consistent quality control, as each wood chip is individually assessed and impurities are removed without human intervention. This automated process reduces the likelihood of errors and increases the reliability of the sorting system.

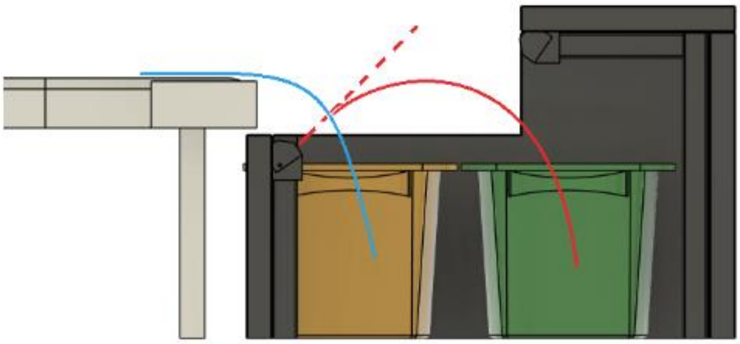

Figure 42: The air nozzles in the system

Integration with Sensor Technologies

The effectiveness of pneumatic air nozzles is amplified by their integration with advanced sensor technologies. The RGB and hyperspectral cameras provide comprehensive data on each wood chip, which is then processed by machine learning algorithms to make accurate sorting decisions. This seamless integration ensures that the pneumatic air nozzles operate with maximum efficiency and precision.

Impact on the Wood Valorisation Process

The deployment of pneumatic air nozzles significantly impacts the wood valorisation process by enhancing the purity and quality of the wood chips. This improvement leads to the production of higher-quality particleboards and MDF boards, which meet stringent market standards and are more valuable. Furthermore, the efficient removal of impurities contributes to the project's environmental goals by reducing waste and promoting sustainable practices.

In conclusion, the use of pneumatic air nozzles in the DigInTraCE project's wood sorting system exemplifies the innovative approach to achieving high-quality wood valorisation. Their ability to precisely remove color-coated wood chips and oversized particles ensures that the wood chips meet the desired purity and size specifications, ultimately contributing to the success and sustainability of the project.

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5. Conclusions

During the first year a valid laboratory to get images from scraps has been developed. Tests in the laboratory has been done using the initial load of scraps obtained from Astigarraga. These tests has been useful to validate the laboratory as a valid test site in order to mimic the final work environment. In the tests more than 85 pictures with scraps has been taken, with about 25-30 scraps in each image. These images has been used as an input for a self supervised model to take out features of scraps and see how the model works.

The scraps has also been catalogued in order to take the most representative properties to create the mosaic, such as size, draw pattern or cut end typology.

However, the need for a greater volume of scraps has been seen. This would allow us to be more certain that the properties selected for the mosaic are appropriate and to see if any more are missing. Furthermore, the more data the computer vision model has, the better it can be trained and the better it will label the scraps.

During the first year of work in the project, a robotic arm has been selected, as well as a camera and vacuum gripper for the end-effector. The first test manipulating the wood scraps from Astigarraga are being carried out in the Tecnalia laboratory, these tests will be performed with manually written trajectories and commands, for testing purposes of the end-effector and robotic process.

In the materials side, the manufacturing process and criteria for the selection of ASTIs by-products have been identified. By-products have been characterized and mechanical pretreatments required to use them in higher value applications have been performed. Also, specifications of the wood chips used for the production of particleboard and information on which panel types from MENEXES would provide suitable chips for the substitution of virgin wood chips in pilot particleboard panels.Shredding into chips, sieving and selected fractions from each type of panels for ICCS`sorting and development)

5.1. Next steps

As next steps, there are tasks that must be implemented before creating the workflow that automates the generation of the mosaic from wood scraps. On the one hand, cut-outs of the images must be generated automatically to be able to extract the embeddings not from the entire image, but from each scrap. This could be done with SAM, for example. Furthermore, once the cut-outs have been generated, the embeddings must be generated and clustered. Once clustered, each cluster must be labeled and associated as far as possible with the properties selected for the generation of the mosaic. With this we would have an algorithm capable of segmenting each scrap and cataloging it in real time, so during the next year these will be the steps to follow.

In the coming months, work will start developing the algorithm for automatically generate the trajectories and commands for the vacuum gripper from the files provided from both the recognition and generative algorithms. Once the system is able to work without human intervention, the Spanish Pilot will be deployed in ASTI facilities where it will take place.

The work on materials treatments to produce high quality fibres will continue.

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Disclaimer of Warranties

This project has used a standard methodology already developed in the DigInTraCE project (Grant Agreement number: 101091801), following EU recommendations. Ad hoc modifications were added to comply with the Grant Agreement conditions for DigInTraCE (Grant Agreement number: 101091801).

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