UNIVERSITÀ DI TRENTO

Cyber physical systems to monitor the efficiency and sustainability of human-centric manufacturing systems

PhD dissertation

Ph.D. candidate:
Andrea Sbaragli

Supervisor:
Prof. Francesco Pilati

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AGENDA

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Introduction

- *Current scenario*
- *Research objectives*

2

Cyber physical system

Unleashing Internet of Things sensors and Machine Learning in human-centric manufacturing systems

- *Digital monitoring of human-centric manufacturing job-shops*
- *Digital monitoring of Reconfigurable Manufacturing Systems*
- *Digital European Assembly Worksheet assessment*

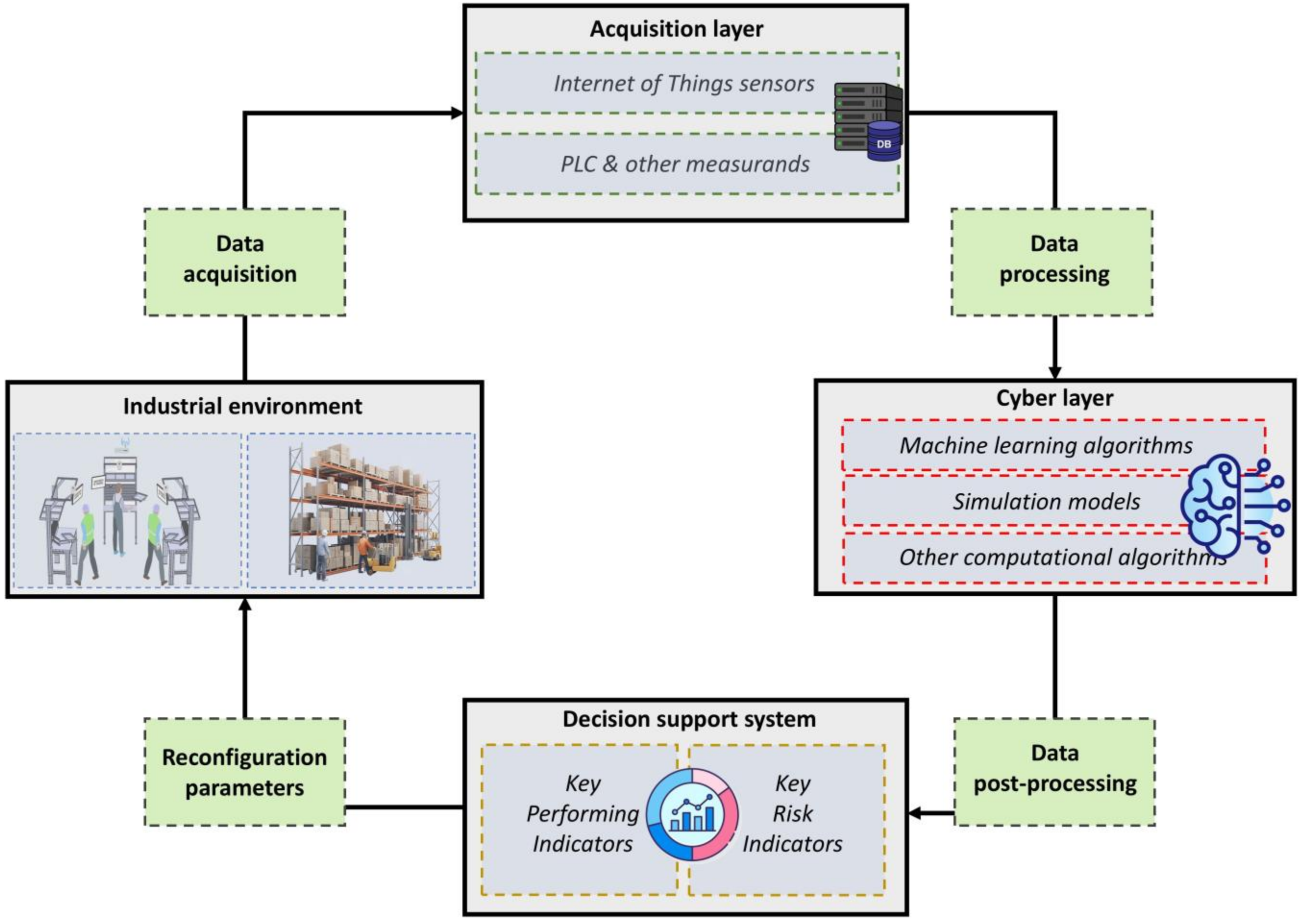
3

Final remarks

- *Conclusions*
- *Further research*

CURRENT SCENARIO

The target is to design **cyber-physical systems (CPS)** to monitor manufacturing systems' **efficiency** and **social sustainability**



Adapted from [Thiede et. al, 2016.]

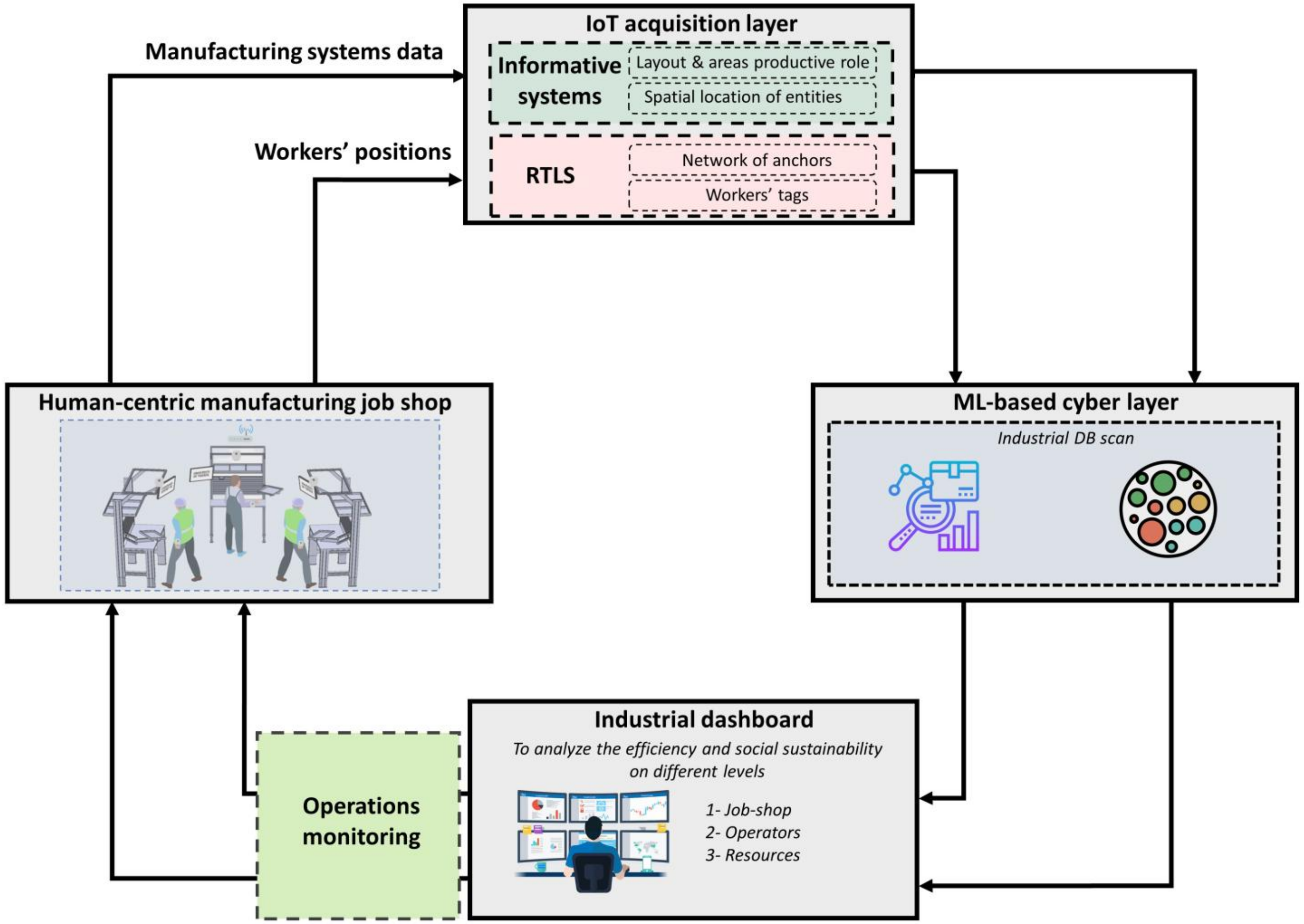
RESEARCH OBJECTIVES

How can **CPS** powered by **Real Time Locating Systems (RTLS)** and **machine learning (ML)** algorithms **digitize** human-centric **processes** executions?

How can **digital ergonomic assessment safeguard** workers' **physical resilience**?

How can **key performance** and **risk indicators (KPI and KRI)** be exploited to **monitor** the **operations** of industrial environments?

Digital monitoring of human-centric manufacturing job-shops



Outline

This digital systems **monitors** the **industrial operations** of human-centric manufacturing job shops by leveraging:

- **Internet of Things (IoT) acquisition layer:** to gather workers' positions and manufacturing systems data
- **ML-based cyber layer:** to detect human process interactions
- **Industrial dashboard:** to evaluate the efficiency and social sustainability from different viewpoints by leveraging KPIs

HUMAN-CENTRIC JOB SHOP

Use case characteristics

1. Medium Italian Company producing mechanical components, machining **cast iron** and **aluminium castings** mainly for the **automotive** and **energy** sector

2. **Pulled production** of a **highly customizable** product portfolio and **small batches**

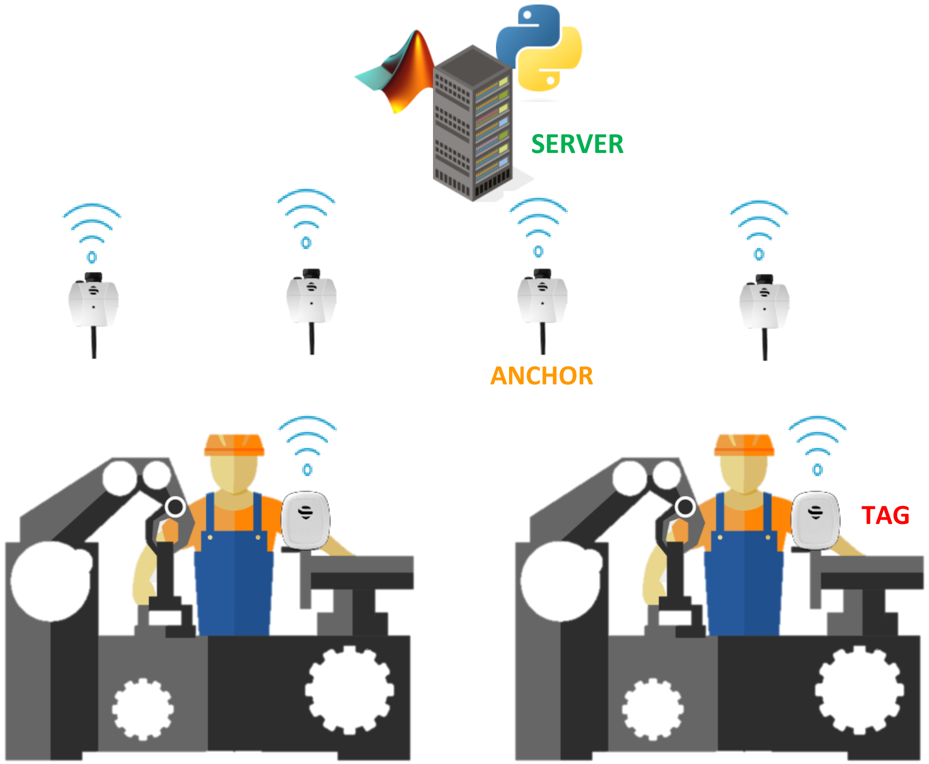
3. **2** dedicated lines **operators** working on up to **3 shifts**. Workers performs both **material handling** and manual **value-added activities**

4. Together with lean managers it was decided to divide the job-shop into 5 different sub-areas:
   - ❖ **Sub-area 1** hosts value-added activities into 2 stand alone machines and deburring and rectification workbenches
   - ❖ The **remaining sub-areas** are storage locations hosting stock-keeping units of products (raw, finished, WIP)

IoT ACQUISITION LAYER

The RTLS network is based on radio-frequencies leveraging the **ultra-wideband** communication protocol

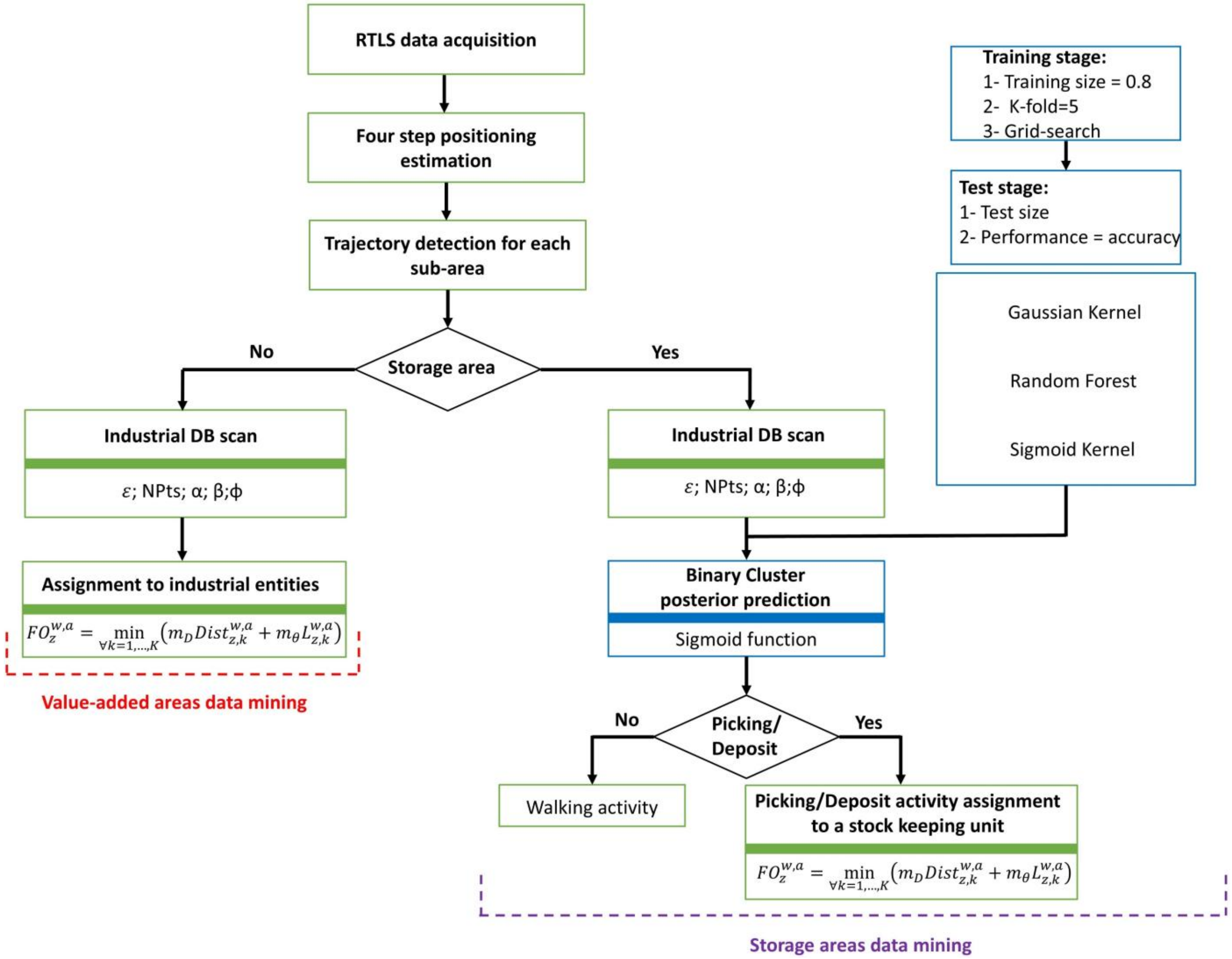
1. **Anchors (ANs)**
2. **Tags**
3. **Server**



Manufacturing systems data are manually mapped and fed as variables into the cyber layer

ML-BASED CYBER LAYER

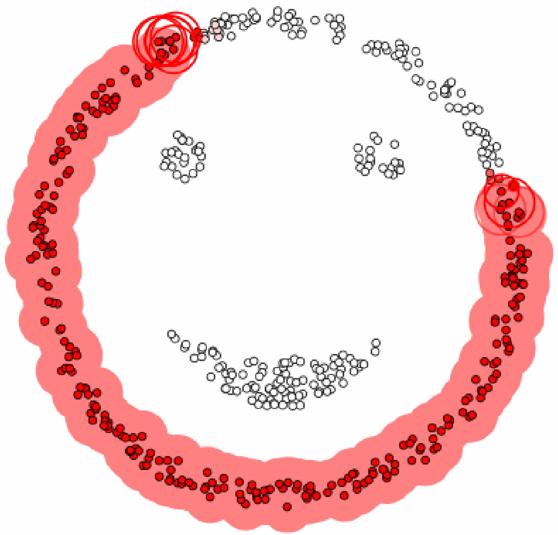
The core objective of the ML-based cyber layer is to detect **human process interactions** in industrial areas based on their productive role



DB Scan algorithm

As a density and unsupervised-based ML algorithm it detects human process interactions based on:

1. ***NPts*: minimum duration** of a human process interaction
2. **ε: distance threshold** between two RTLS data to consider them part of the same process interaction



What if two human process interactions occur in the **same spatial area** but during **different time windows**?

What if two human process interactions are affected by the **measurement noise** or the **uncertainty of the human factor**?

VS

Industrial DB Scan algorithm

1. Positioning points of human process interactions must be **temporally consecutives**

$$p^{w,a}_{i,f',q} - p^{w,a}_{i,f'+1,q} = \delta t, \forall\, p^{w,a}_{i,f',q}\,,\; p^{w,a}_{i,f'+1,q} \in S^{w,a}_{i,q}$$

Human process interactions are also distinguished by **geometrical centers**

$$Ox^{w,a}_{z,i} = \frac{\sum_{f=f'}^{f^*-1} px^{w,a}_{i,f',z}\left(ts^{w,a}_{i,f'+1,z} - ts^{w,a}_{i,f',z}\right)}{\sum_{f=f'}^{f^*-1}\left(ts^{w,a}_{i,f'+1,z} - ts^{w,a}_{i,f',z}\right)}$$

2. When two consecutive interactions can be merged together?

AND

$$ts^{w,a}_{i,f',z} - ts^{w,a}_{i,j^*,z+1} \leq \alpha$$

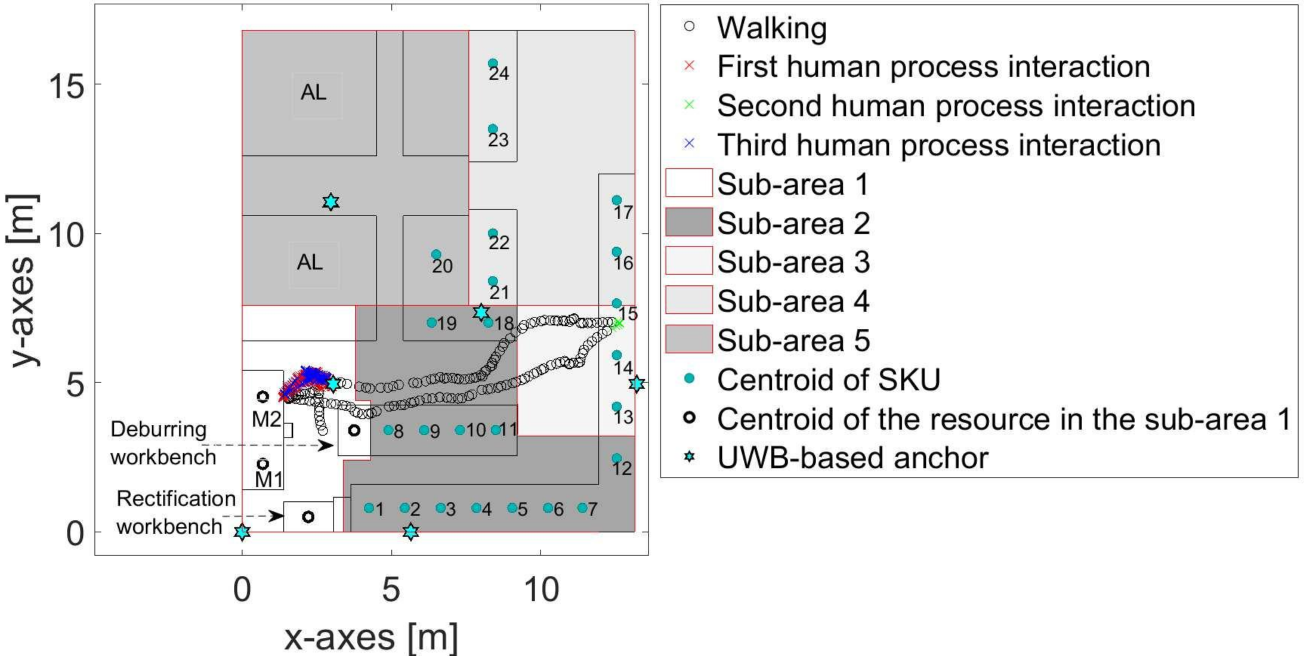
$$EuclideanDistance(p^{w,a}_{i,f',z}, O^{w,a}_{z+1,i}) \leq \beta$$

OR

$$EuclideanDistance(p^{w,a}_{i,f',z}, p^{w,a}_{i,j^*,z+1}) \leq \phi$$

ML-BASED CYBER LAYER

Example on a worker's trajectories



Performances

Sub-area 1

Detection accuracy: 82%
Duration mean delta: 2.69 sec (14.1%)
Assignment to resource: 88.1%

Storage areas

Detection accuracy: 76.4%
Assignment to SKU: 100%

Production managers to evaluate the **efficiency** and the **social sustainability** of the human-centric job shops through several **KPIs**

Resource
- Utilization ratio
- Workers' interactions

Job shop
- Heat map of picking/deposit activities
- From-to-chart

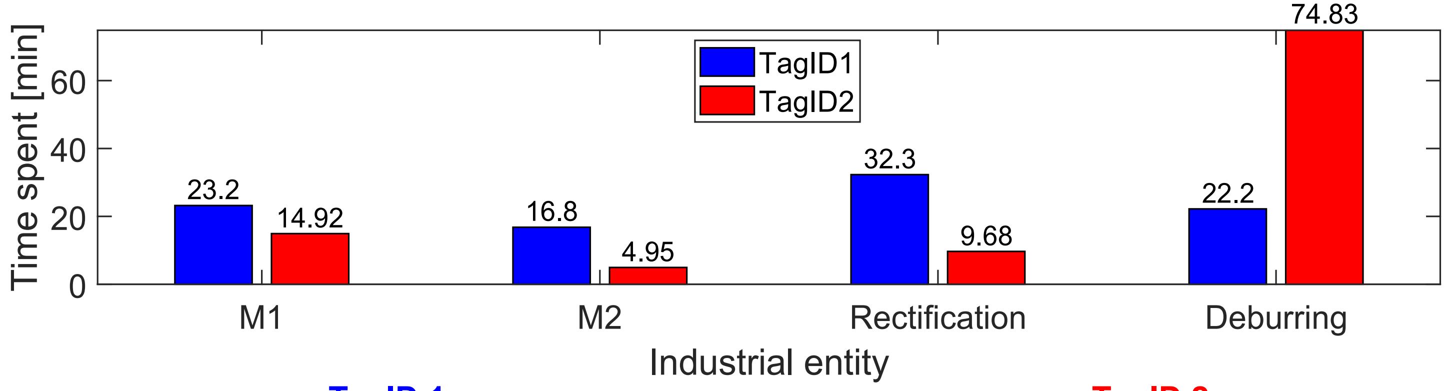
Operator
- Distances travelled in material handling
- Number of interaction with SKUs

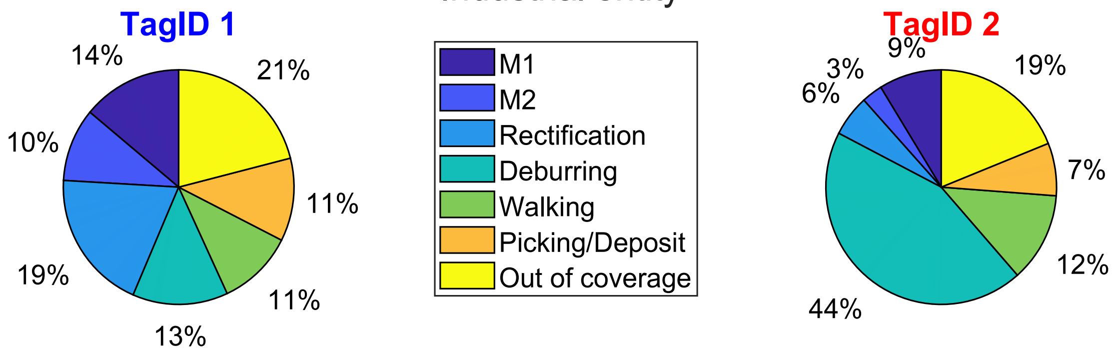
The following discussion is based on a portion of the working shift from 9.45 to 13:00 on the 3rd of March 2022

INDUSTRIAL DASHBOARD

Resource level

This detail level enables **workers' activity segmentation** over the monitored period





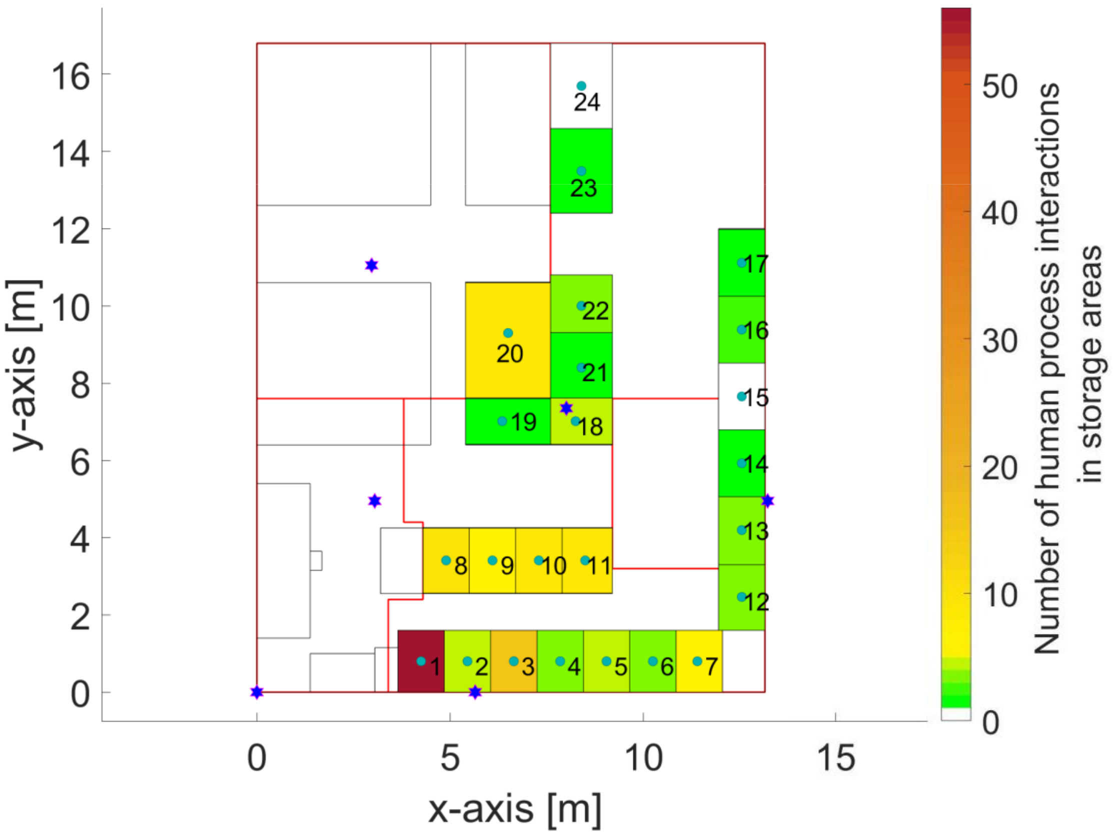
- Workers have completely **different** working **routines**
- TagID1 and TagID2 interacts with sub-area 1 entities the 56% and 62% of the entire time window
- **Low utilization** ratio of resources. **Greatest** ratio for the deburring equal to **55.9%**
- **Good practice:** no resource is simultaneously **occupied**

How workers different activity distribution affects picking/deposit activities?

INDUSTRIAL DASHBOARD

Job shop level

This viewpoint suggest that storage areas are distinguished by a **poor material allocation**



The farthest SKUs of the sub-area 2 (5,6,7,11,12,18) hosts together 24 picking/deposit activities (18,9% over the total occurred)

Including the SKUs of other areas this metric account for the **30%**

Almost a third of picking/deposit activities is underperforming

Let's group SKU number into **five different categories** based on their **distance** with the **value-added area** (sub-area 1)

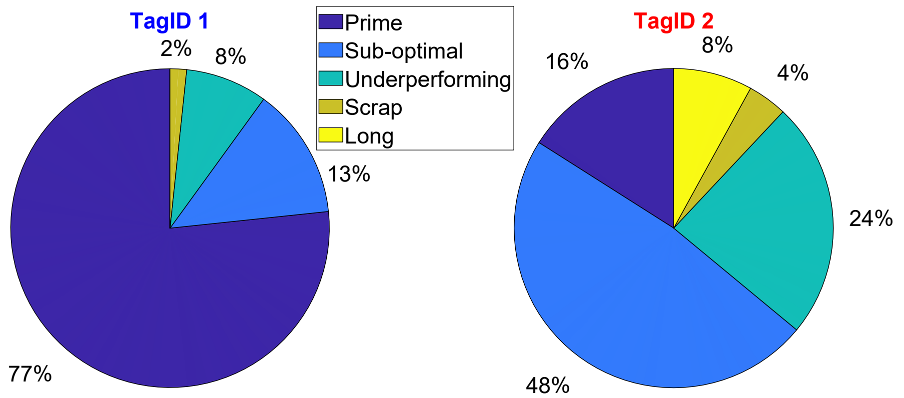
Class	SKU Number
Prime	1,2,8
Sub-optimal	3,4,9,10,19
Underperforming	5,6,7,11,12,18
Long	13-17, 21-24
Scrap	20

How this **inefficiency** propagates affects workers' material handling?

ML-BASED CYBER LAYER

Operator level

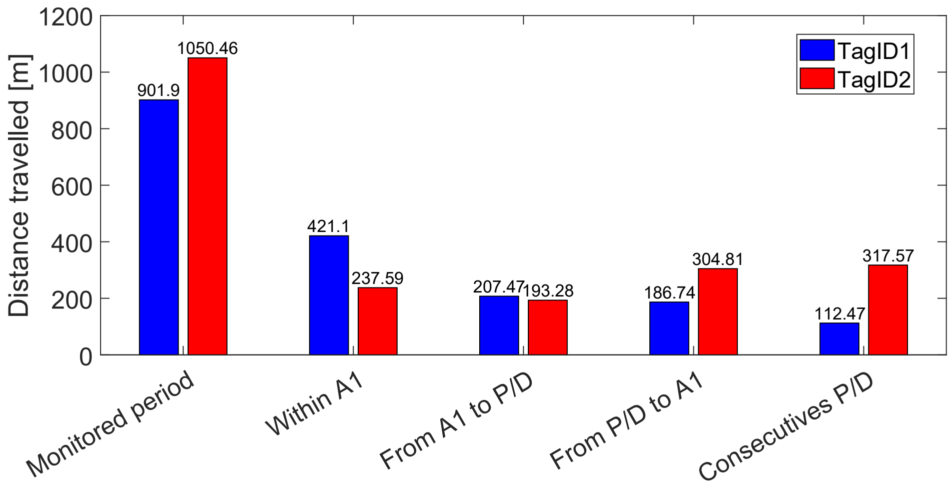
This final level of detail suggest how **material allocation inefficiencies** affects workers logistic activities



The 90% of picking/deposit activities for **TagID1** involves the closest SKU classes with sub-area 1

TagID2 performs more than the 30% of logistic activities with the farthest SKU classes

This imbalance is reflected into distance traveled but how much?



Scenario From A1 to Picking/Deposit (PD) activities

TagID1: 60 flows

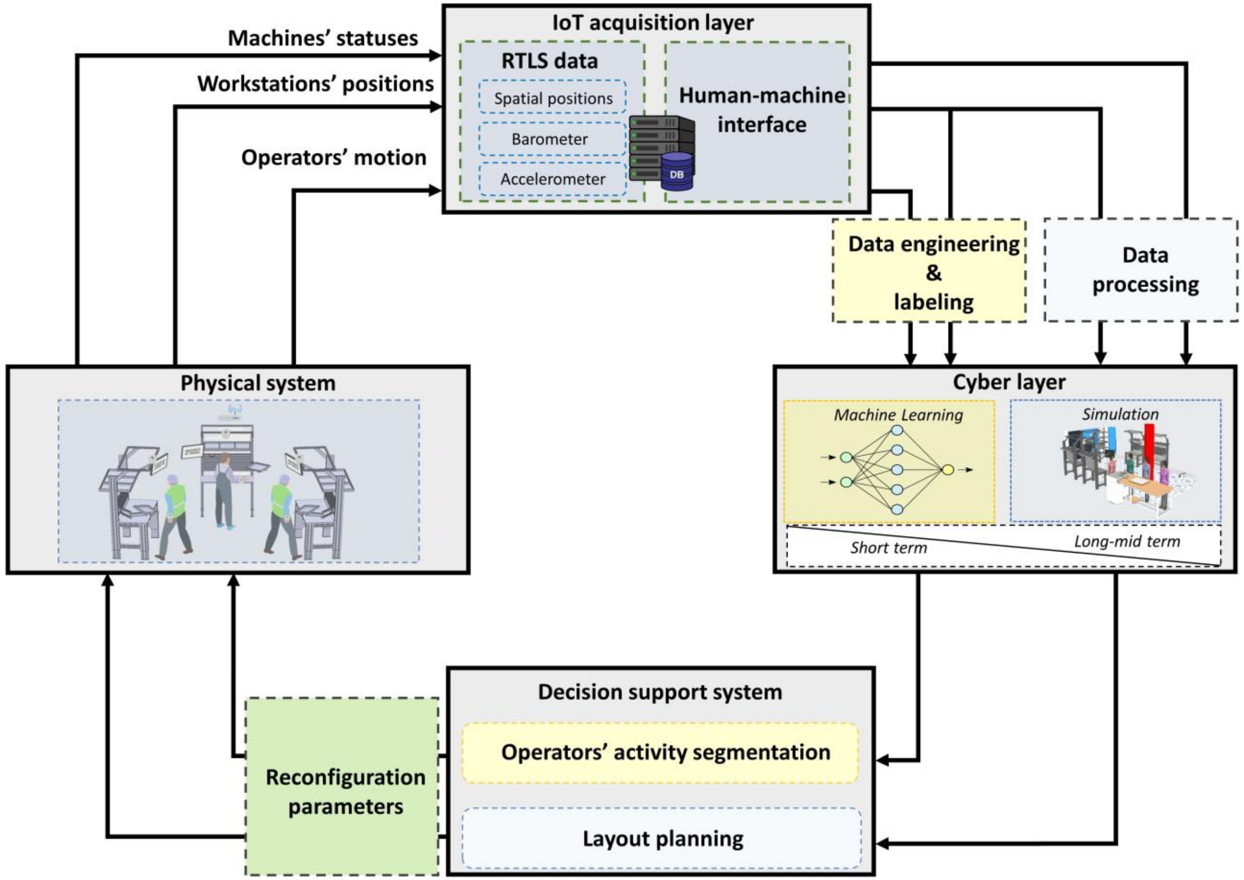
TagID2: 25 flows

Mean values suggest that **TagID2** travels **2.24 times** the meters travelled by **TagID1**

TagID2 is socially disadvantaged in picking/deposits activities

Digital monitoring of Reconfigurable Manufacturing Systems

RMS are designed at the outset for rapid change in structure, as well as in hardware and software components to quickly adjust production capacity and functionality within a part family in response to sudden changes in market or in regulatory requirements (Koren et. al, 1999).

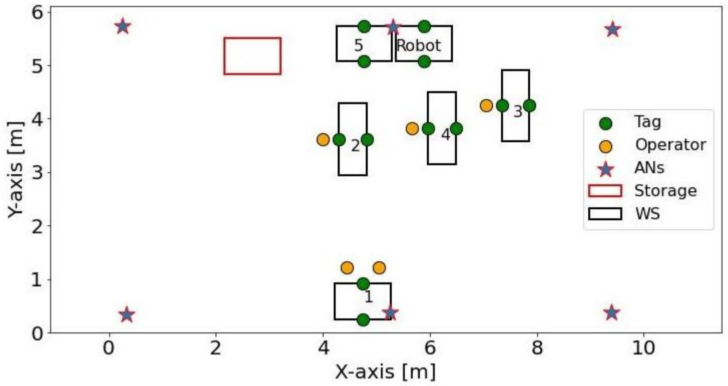


Outline

This layout and task insensitive digital systems **monitors** the **industrial operations** of human-centric RMS by leveraging:

- **IoT acquisition layer:** to gather workers' motion patterns and industrial resources positions in production set-ups
- **ML-based cyber layer:** to segment workers' activities and differentiating them into value added and non-value added
- **Decision Support System:** to evaluate the efficiency and the interdependencies of production set-ups

Use case characteristics



1. Industrial-related production environment that assembles a **medical spinal prosthetic** leveraging a **variable** number of **resources** and **workers**

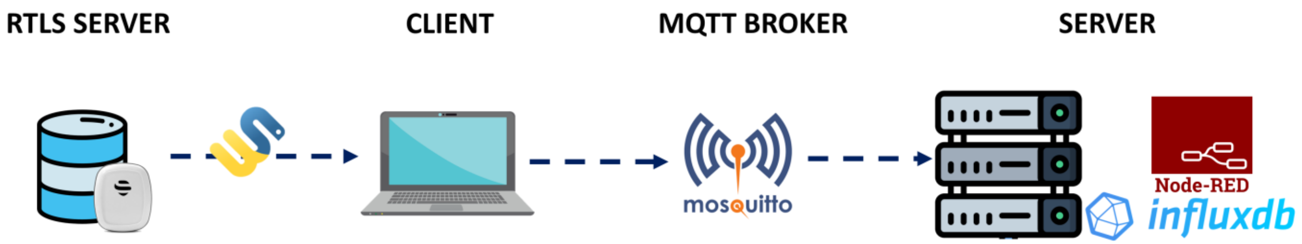
2. Production set-ups produces **3 prosthetic** with a duration between **15** and **20 minutes**

3. Production process involves several **manual tasks** ranging from **glueing** and **screwing** to **quality inspection**

4. Experimental campaign involved **40 workers** and **8 production set-ups** achieving almost 1 million of dataset samples

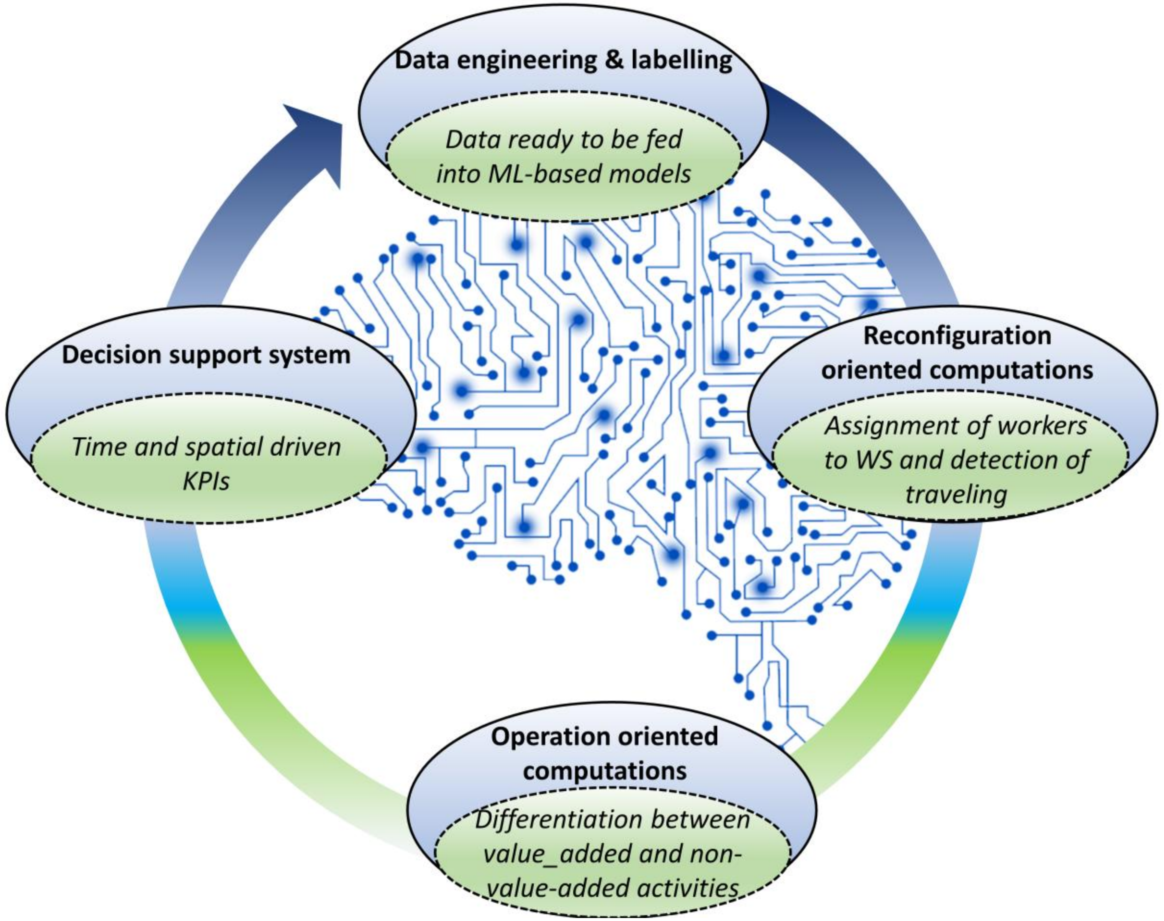
IoT ACQUISITION LAYER

The **RTLS-based** IoT acquisition layer is deployed to monitor workers' motion patterns and industrial resources positions



ML-BASED CYBER LAYER

The core objective of the ML-based cyber layer is to detect **segment workers' activities** and differentiate these between **value added** and **non-value added**



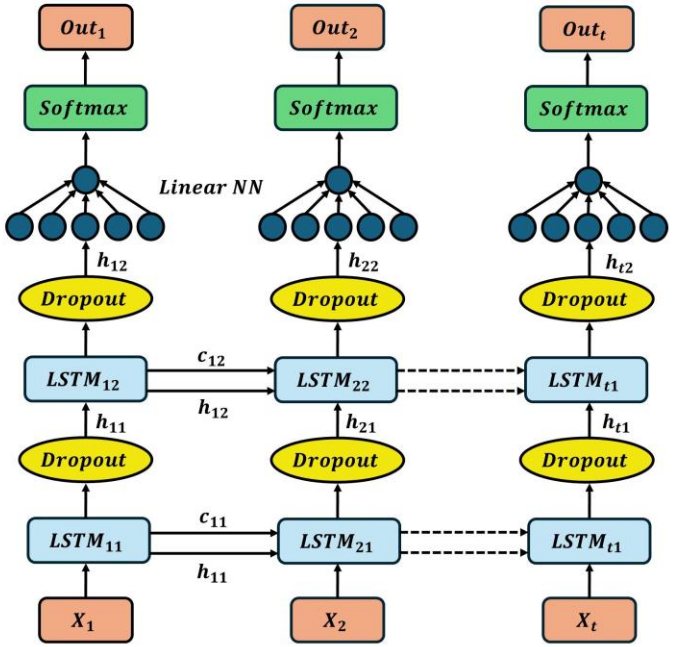
Processing steps

- **<u>Data Engineering & labelling:</u>** this step increases the dataset dimension by engineering additional features from the acquired motion patterns of workers. In particular, the dataset is distinguished by a **relative coordinate** system between workers' and industrial resources positions.
- **<u>Reconfiguration oriented computations:</u>** this ML-based algorithm performs a layout and operator-insensitive classification of **logistic activities** and assignment to **industrial resources**
- **<u>Operation oriented computations:</u>** this last ML-based step consists of a resource-specific approach to classify **value-added and non-value-added** operations
- **<u>Decision support Systems:</u>** computes **KPIs** to monitor activities execution of production set-ups

ML-BASED CYBER LAYER

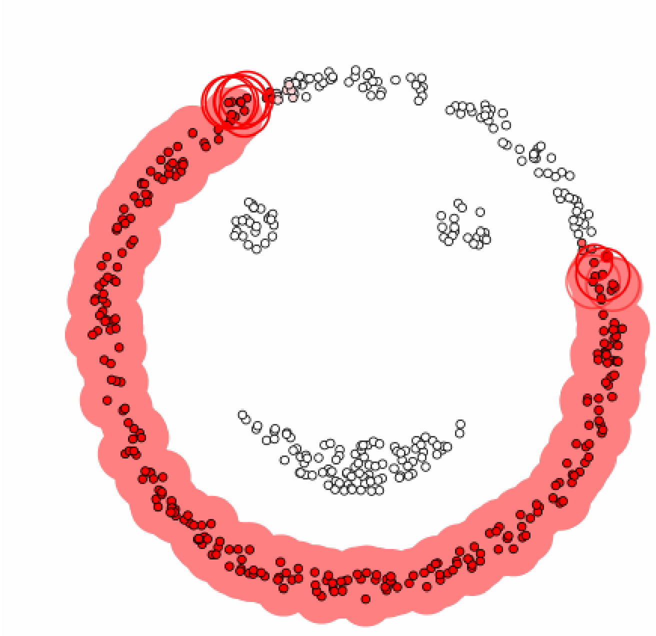
The **reconfiguration-oriented computations** benchmark three ML-based algorithms

LSTM-based Neural Network



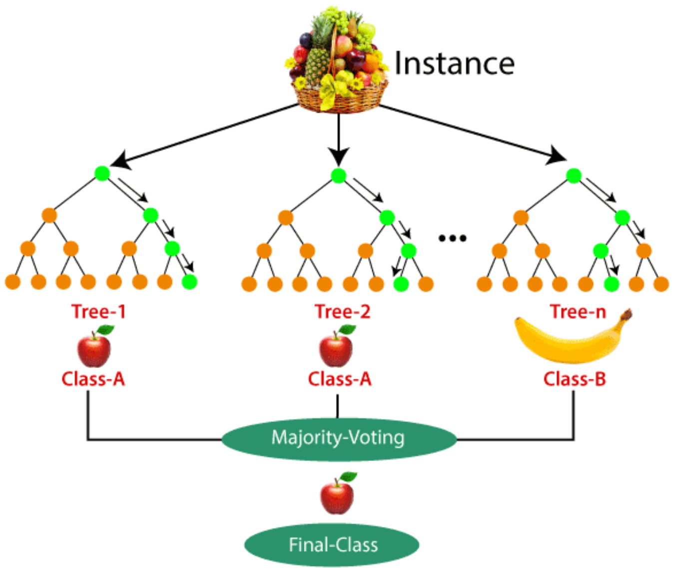
VS

Industrial DB scan



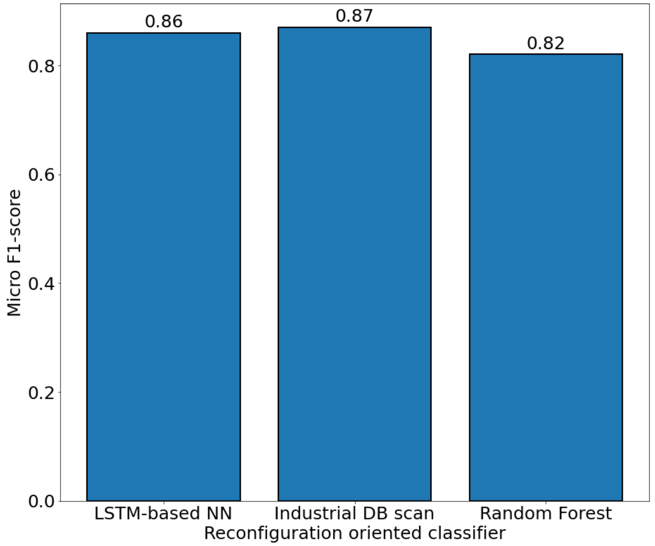
VS

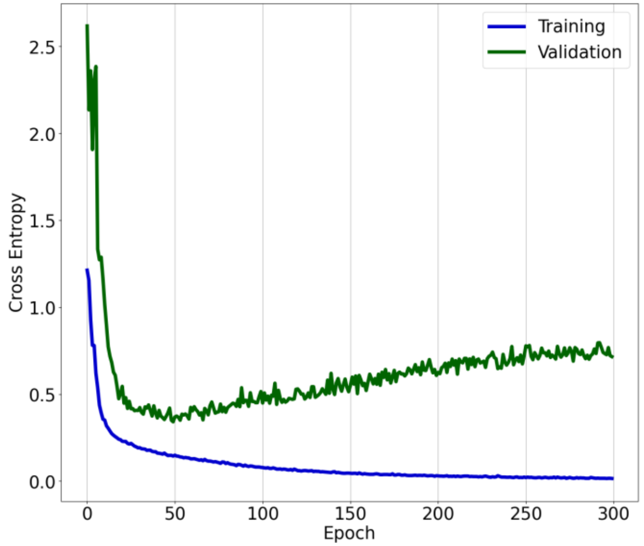
Random Forest

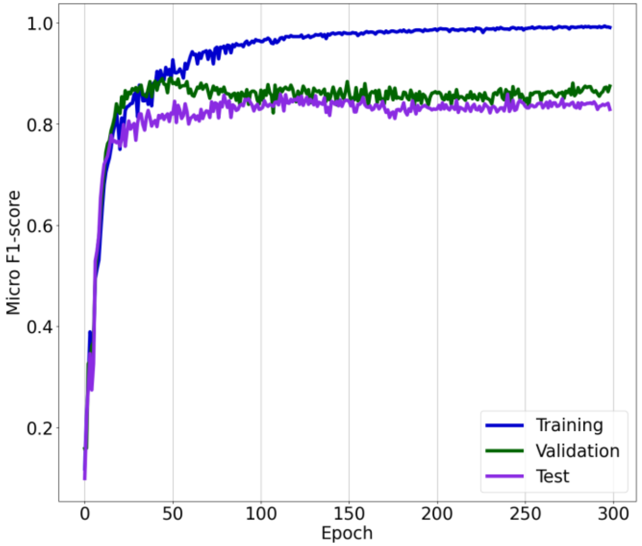


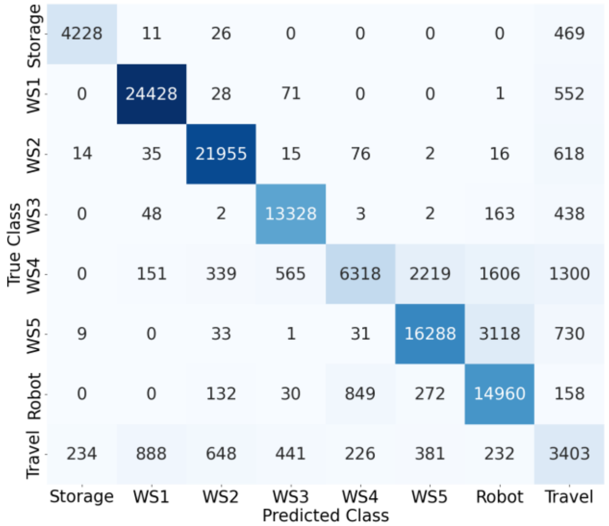
ML-BASED CYBER LAYER

The **LSTM-based architecture** is the most performing algorithm for the reconfiguration-oriented computations









Vast majority of classes are distinguished by **F1 scores** greater than **82%**

F1 scores for Storage, WS3, WS2 and WS1 above **92%**

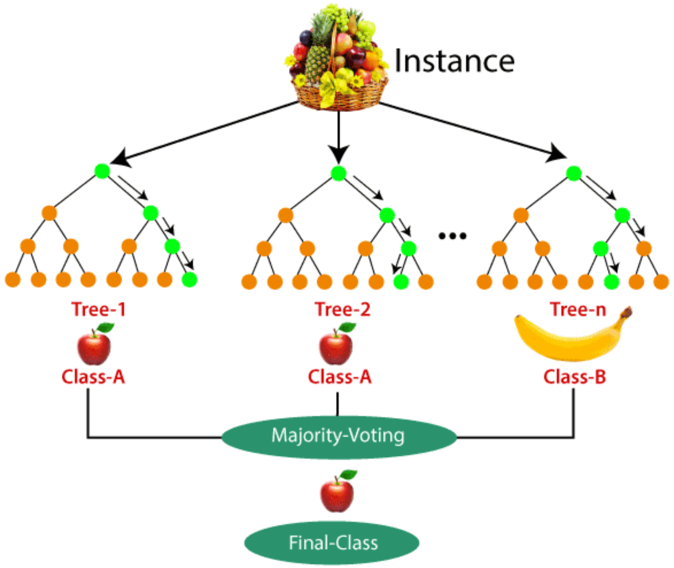
The vast majority of **misclassificaiton** is related to WS4 and Travel classes

WS4 is hardly adopted

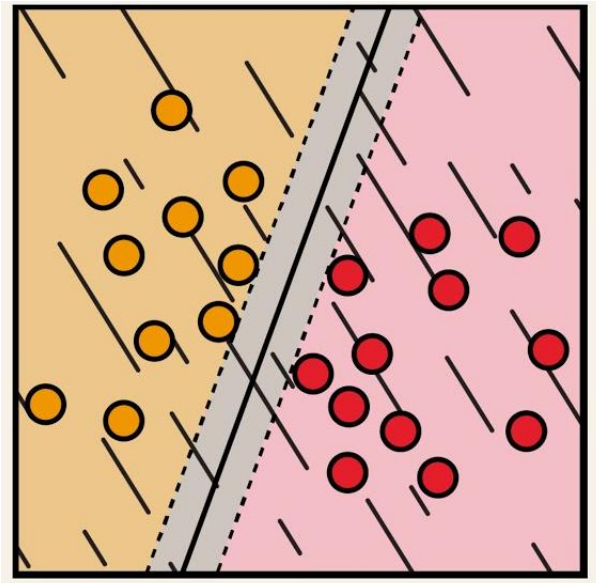
Narrowed distances among resources

The **operation-oriented computations** benchmark three basic ML-based classifiers

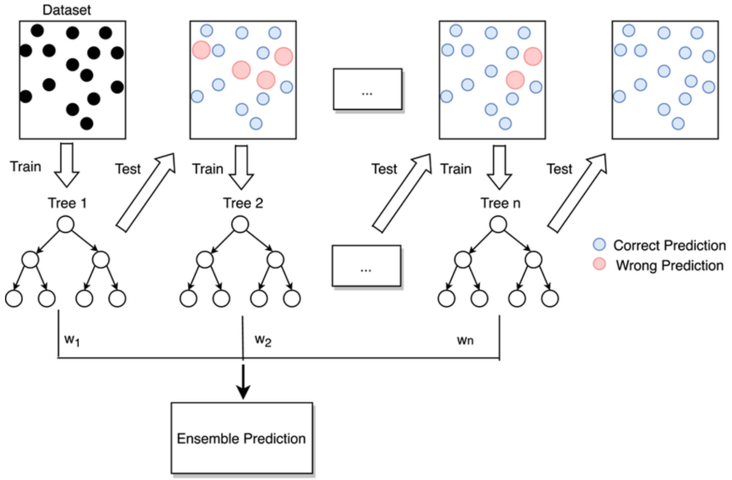
Random Forest



Support Vector Machine

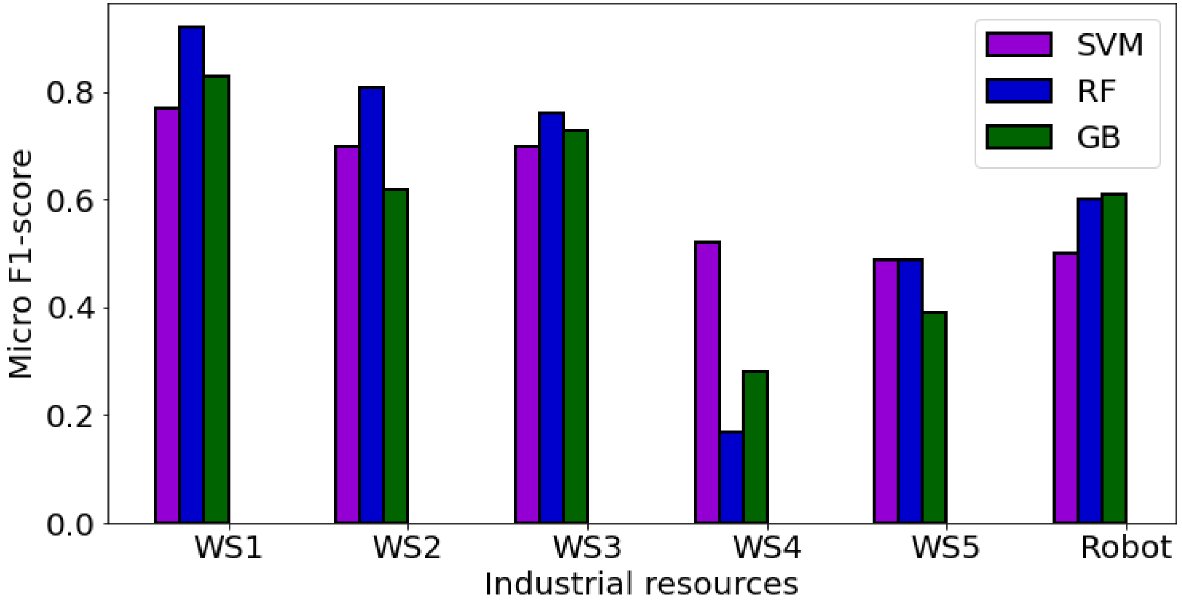


Gradient Boosting



ML-BASED CYBER LAYER

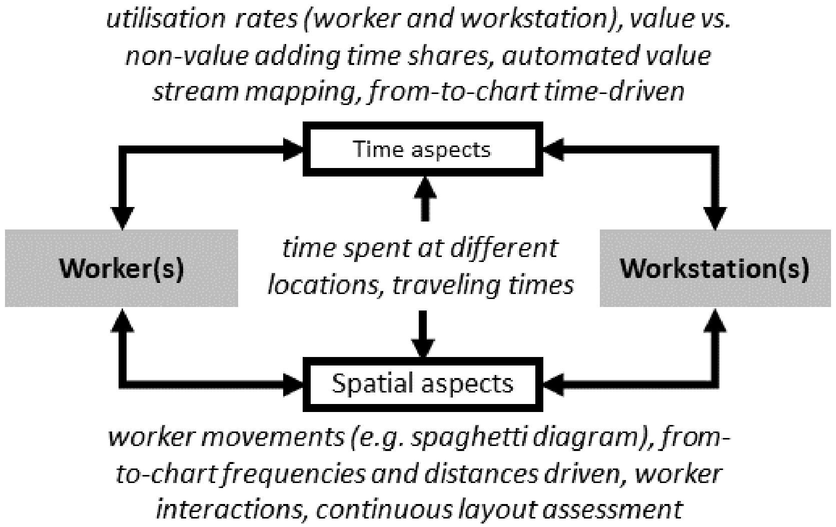
The **operation-oriented computations** are challenged in detecting value added activities by the case study



The **Random Forest** is the most performing classifier for WS1, W2 and WS3 with **F1-scores** ranging from **76%** to **92%**

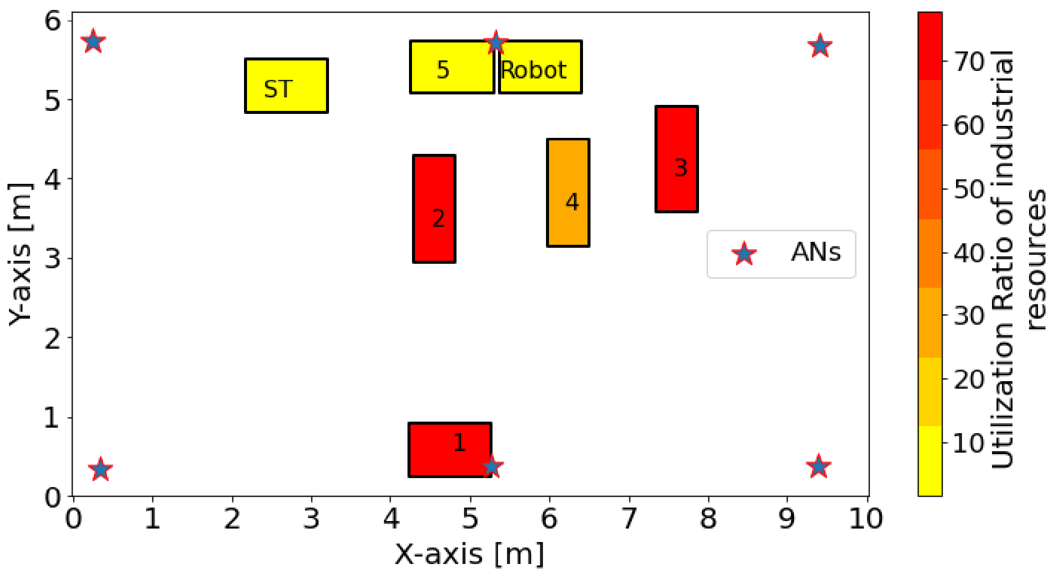
'he remaining resources presents **F1-scores** below **60%** due to pretty **static** workers' **motion patterns**

Production managers to evaluate the **efficiency** and the **social sustainability** of the human-centric job shops through several **KPIs**



The following discussion is based on the 7th **production** set-up lasting 16 minutes

The industrial operations monitoring starts by analysing the **resources' utilization ratio**



WS1 has the greatest utilization ratio equal to **77.82%**

WS2 and **WS3** follows with shares ranging from **70.22% to 72.31%**

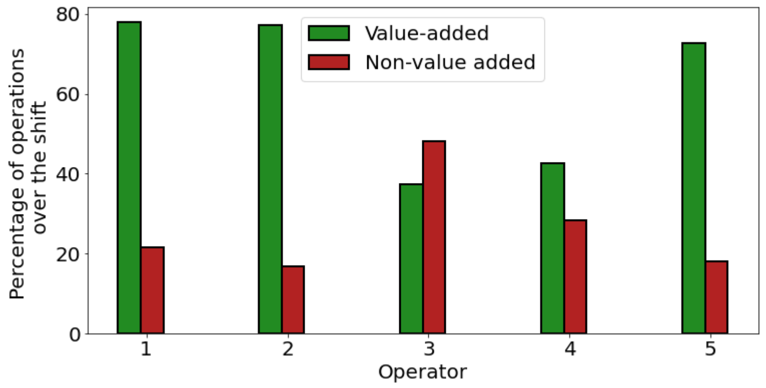
WS4 is a jolly workstation to support WS2 and WS3**. Low** utilization ratio below **40%**

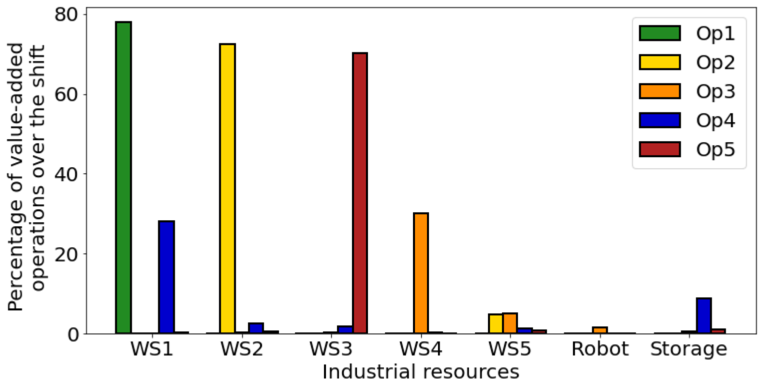
The remaining resources do not exceed **15%**

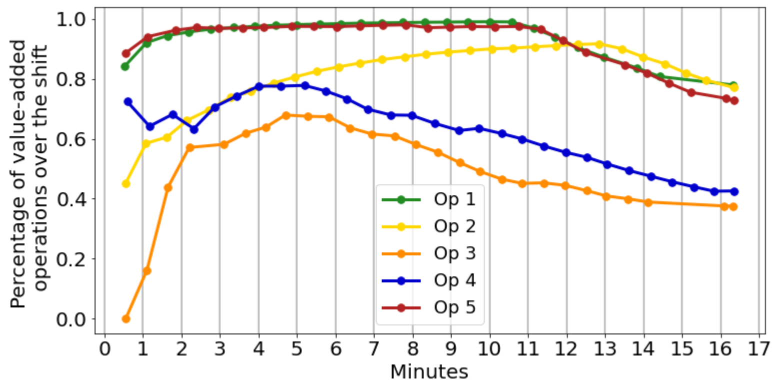
How resources utilization ratio affects workers' labour?

DECISION SUPPORT SYSTEM

Narrowing the focus on **human-centric KPIs** provide additional information on **set-up efficiency**







Op1, **Op2**, and **Op5** register shares of value-added operations greater than 72%

Op3 and **Op4** have shares below **43%**

Op1, Op2 and Op5 value-added operations never below **72%** are limited to **WS1, WS2 and WS3**

Op3 suggests that low productivities of **WS4** are compensated with **WS5** and **Robot** activities

Op4 interacts with all resources, where an **8.77%** of time is in the storage location

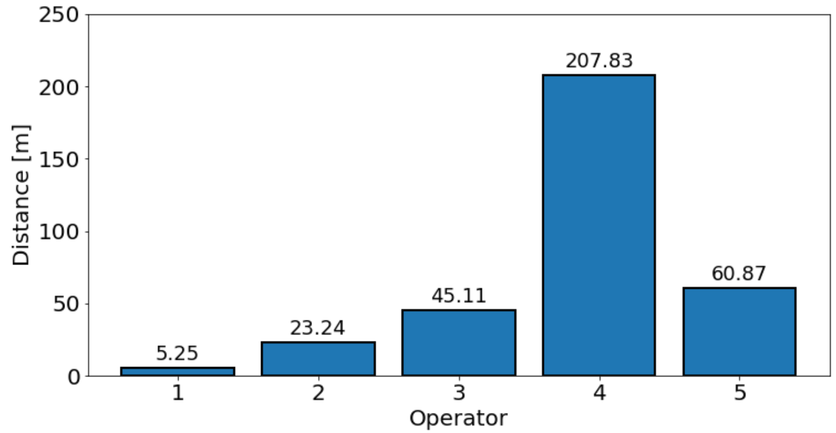
Op1, Op2 and Op5 present a share of value-added operations greater than **80%** for the vast majority of the shift

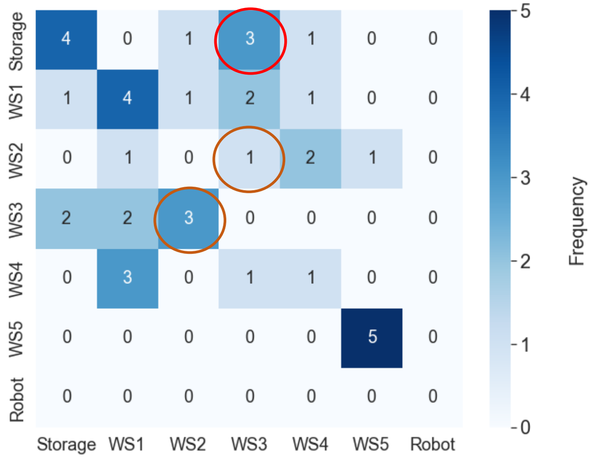
Potential overallocation of workers

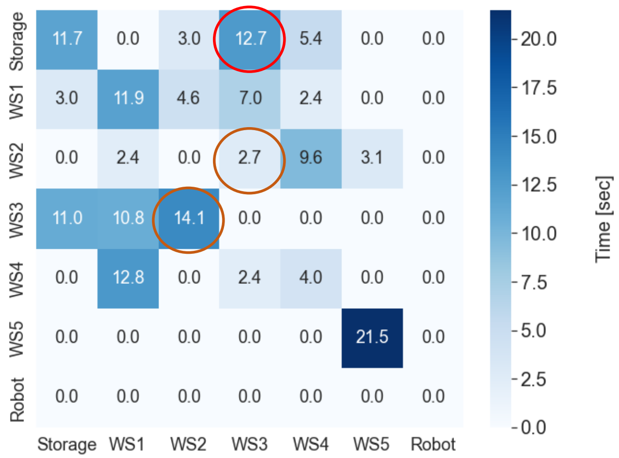
How are logistics activities assigned to workers?

DECISION SUPPORT SYSTEM

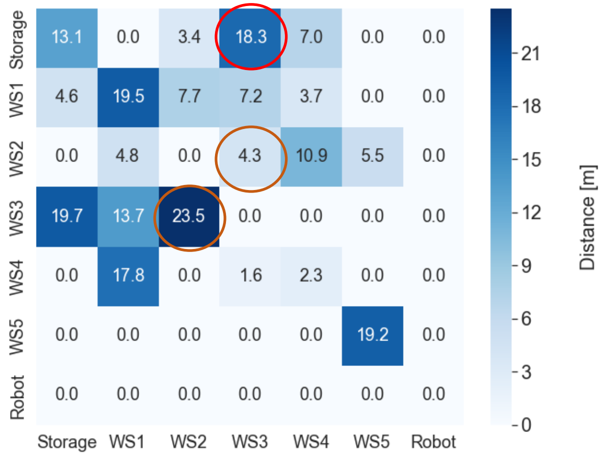
Shifting the focus to **logistic activities** it's possible to evaluate the **social sustainability** of production set-ups



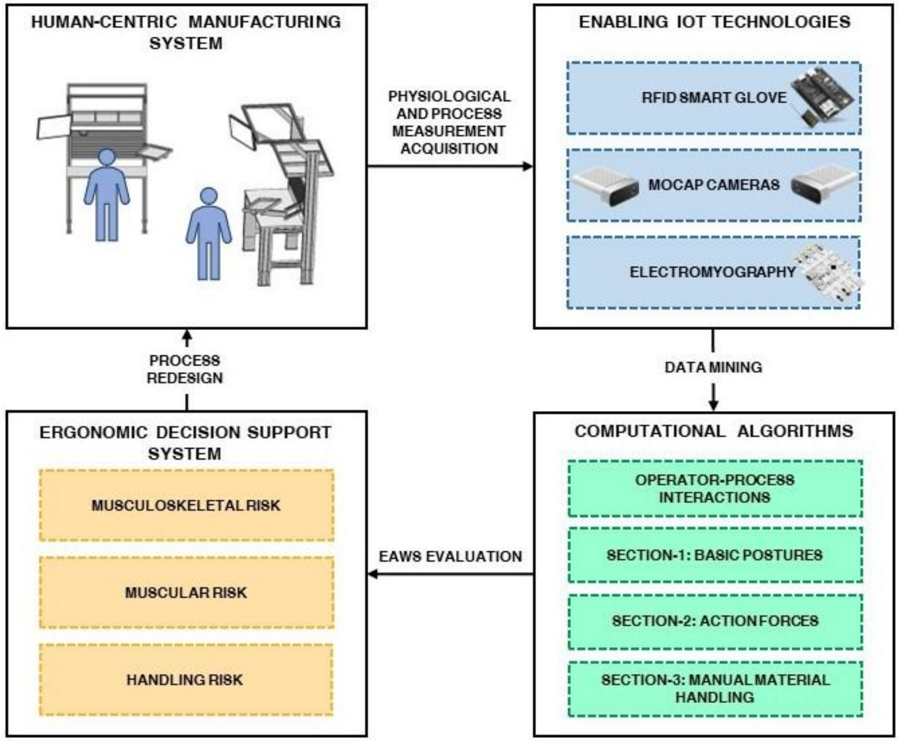




- **Op4** presents the largest share of logistic activities
- **Op4** has Several **flows** involving **WS1, WS2 and WS3**
- Increasing buffer sizes would reduce **these metrics**
- Bringing closer **WS2** and **WS3** would reduce **these values**



Digital European Assembly Worksheet assessment

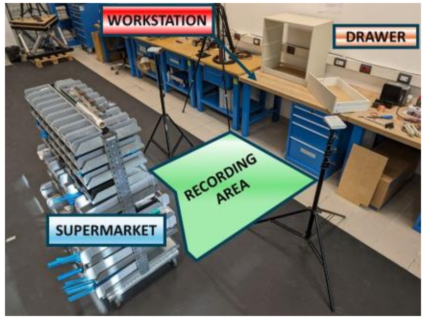


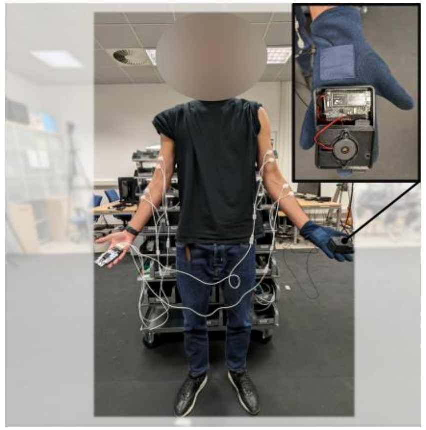
Outline

This **operator and task insensitive** digital systems **evaluates** the **workers' physical resilience** during tasks execution:

- **IoT acquisition layer:** to identify tasks and tools as well as workers postures and muscular activations
- **Computational algorithms:** to digitize the EAWS index
- **Ergonomic Decision Support System:** to evaluate workers' safety through EAWS-informed KRIs

HUMAN-CENTRIC ASSEMBLY LINE





Use case characteristics

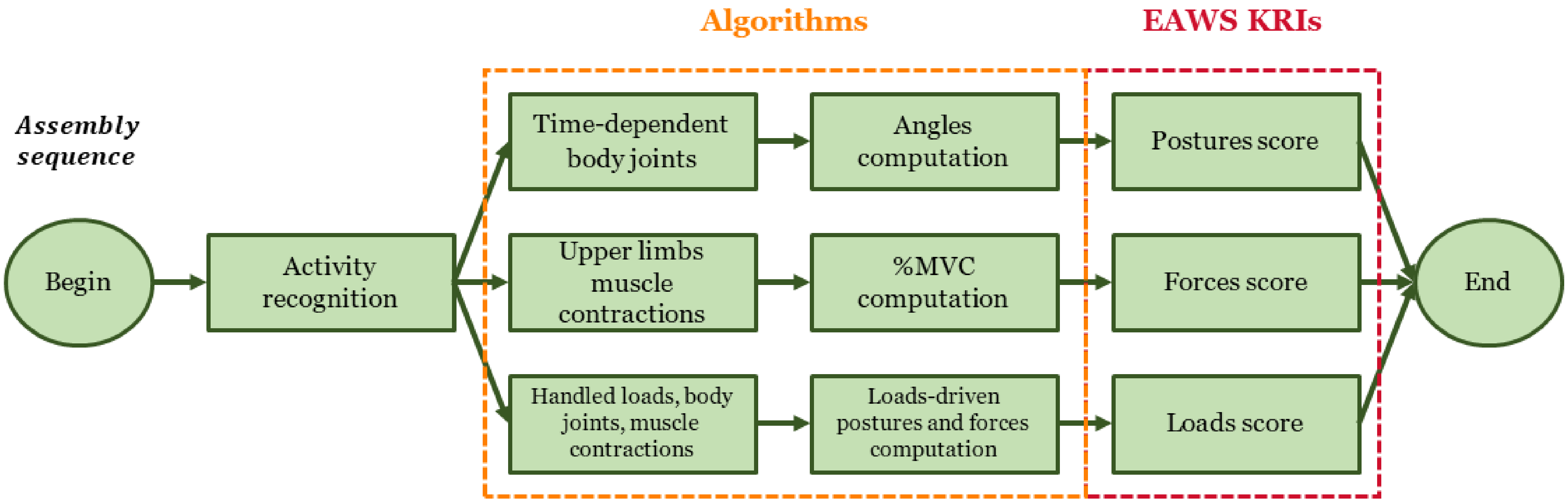
1. Industrial-related production environment that assembles an **IKEA drawer** in **22 tasks** involving manual and tool-aided operations

2. Assembly tasks targets the **mounting** of the furniture **structure** till the **insertion of drawers**

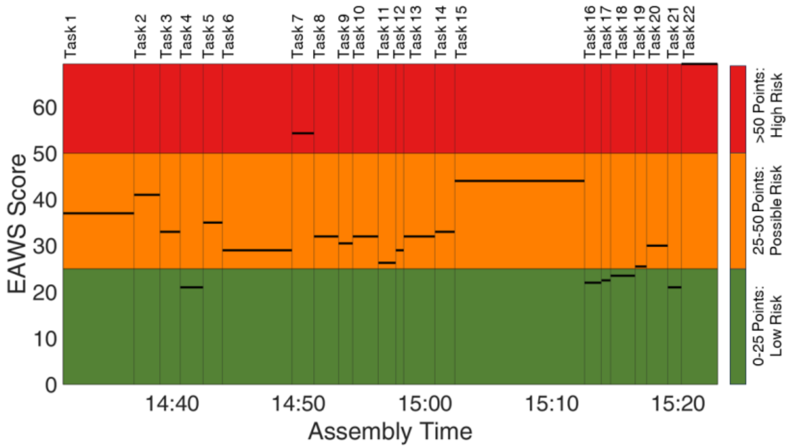
3. **Kinect** cameras placed at **known location**, pre-gelled **sEMG** electrodes on **upper limbs** and **RFID** antenna on **dominant hand**

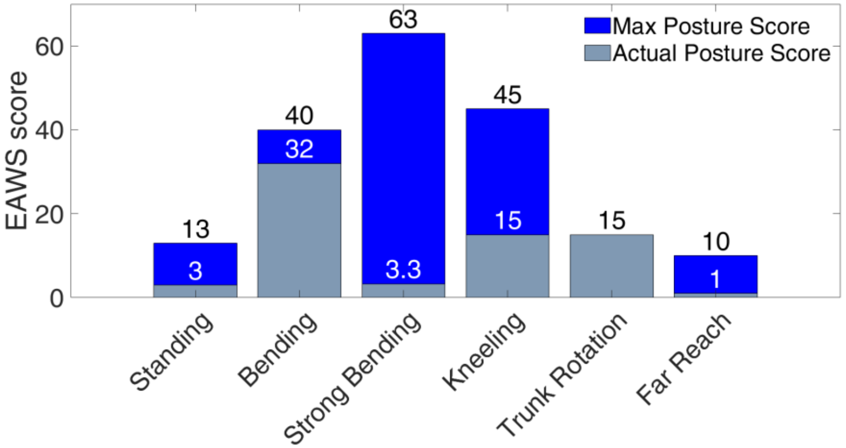
4. Experimental campaign involved **3 workers** and **5 assembly each**

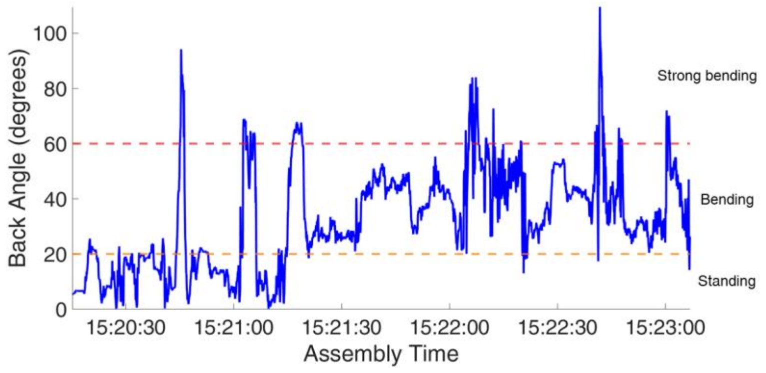
COMPUTATIONAL ALGORITHMS



Section 1 – Basic Postures







Activity driven KRI points out the musculoskeletal riskiest task

Tasks #22 registers **69.3** EAWS points

Frequent **bending** scenarios occurs in while the workers is **fitting drawers** into the furniture structure

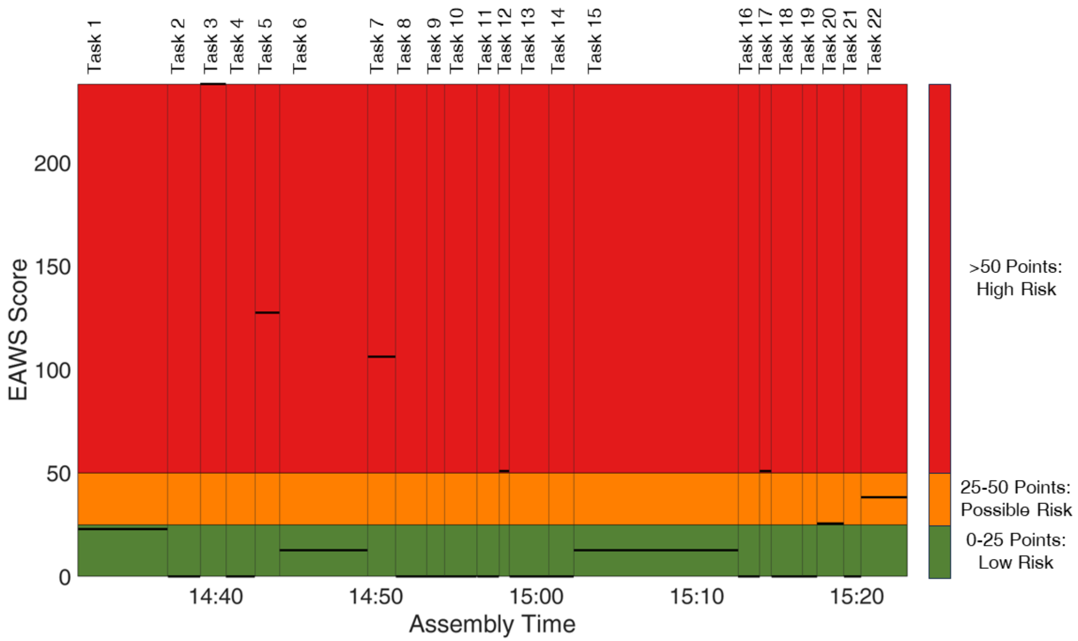
More than **70%** of tasks falls in the higher categories risk

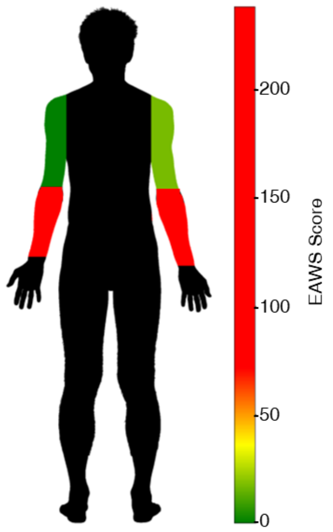
Bending, **Kneeling** and **Trunk Rotation** have the highest impact

More than **70%** of task time is dedicated to bending scenarios

ERGONOMIC DECISION SUPPORT SYSTEM

Section 2 – Action Forces





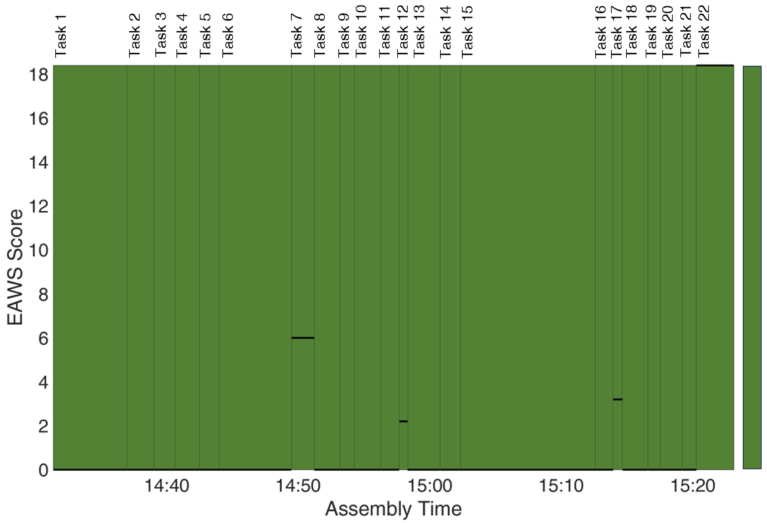
Approx. **70%** of tasks fall within the low-risk band.

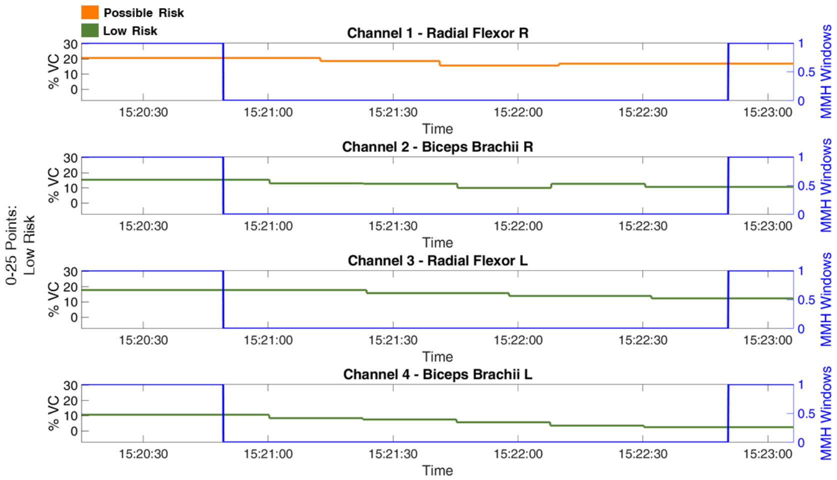
Radial flexors are the most stressed muscles accounting for **%VC** ranging from **40%** to **67%**

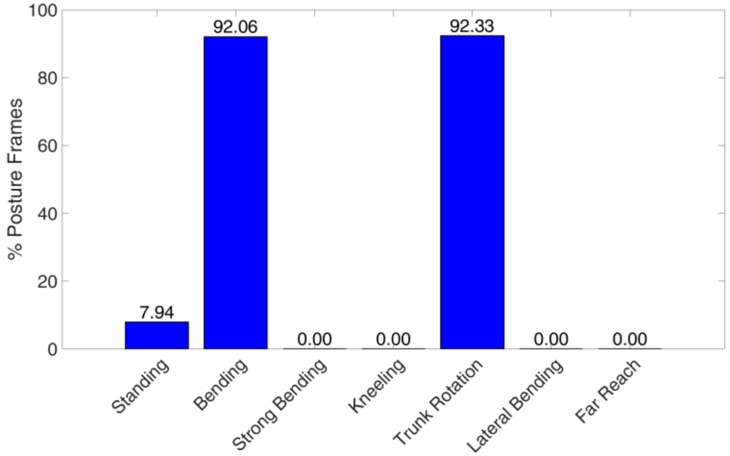
Tasks #3 registers **238** EAWS points while dowels are manually fitted into dowels with a duration of 95 seconds

Forearms accumulates **238** and **127.5** EAWS points

Section 3 – Manual Material Handling







- **All tasks** falls in the **low-risk** region
- Radial flexors %VC contributes to higher scores
- Despite **Task #7** carries the highest load equal to **7 kg,** Tasks #22 has the greatest risk accounting for **18.4** EAWS points
- **Trunk Rotation** and **Bending** are the most hazardous scenarios with average angles equal to **31.3°** and **29.7°**

CONCLUSIONS

? CPS powered by RTLS and ML

- RTLS: Enhance processes visibility
- ML: valid approach to detect process interactions and segment workers' activities

? Digital ergonomic assessment

- Ergonomic indexes: managerial tool to evaluate workers' physical resilience
- IoT and computational algorithms: task and operator insensitive automatic assessment

? Dashboards

- KPIs: efficiency and social sustainability monitoring of industrial operations
- KRIs: workers' physical resilience monitoring

FURTHER RESEARCH

1. **Improve classification performances** for value-added and non-value-added tasks and logistic activities
2. Detect carried **loads** in **logistic activities**
3. Fully **automate** the **EAWS** assessment (e.g., Section 4 – Upper Limb Load)
4. Feed **production /managerial data** sources (e.g., MES data)
5. Scale the systems to achieve **human digital twins**
6. Integrate **heuristic algorithms** to optimize industrial **operations**

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Cyber physical systems to monitor the efficiency and sustainability of human-centric manufacturing systems

Thank you for your attention

Ph.D. candidate:
Andrea Sbaragli

Trento, January 10th, 2025