Smart Digital Twins for Industry 4.0

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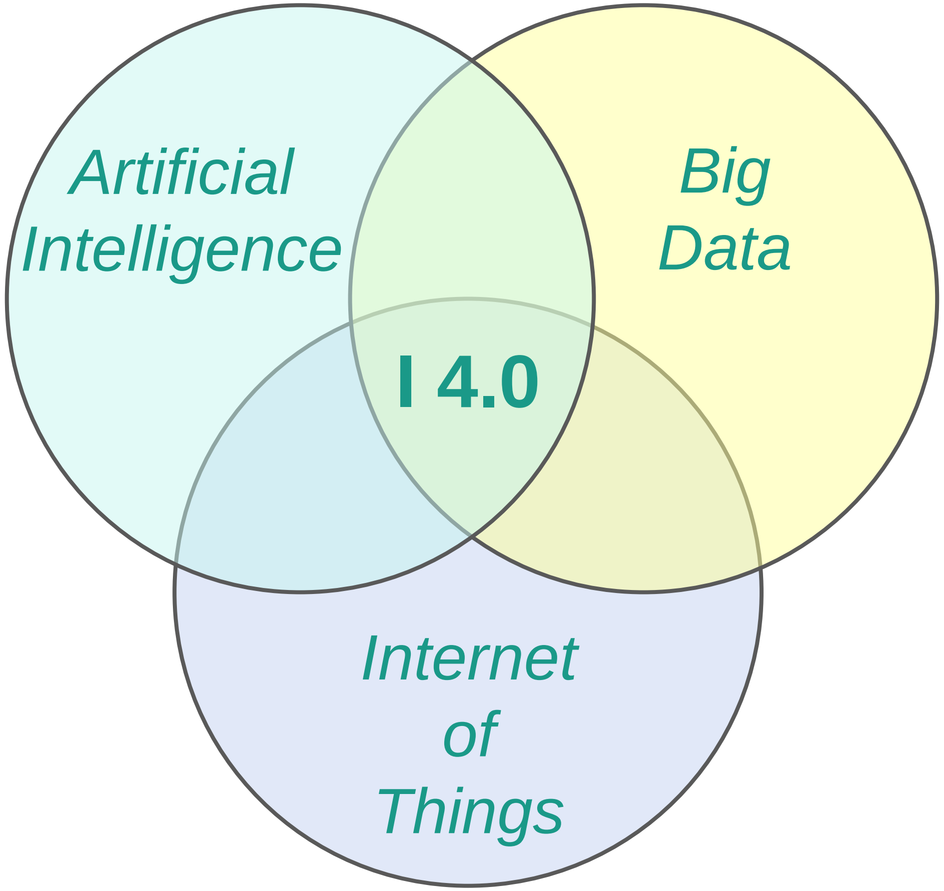
UNIMORE
UNIVERSITÀ DEGLI STUDI DI MODENA E REGGIO EMILIA

Dissertation context



- Context: Industrial digitalization.
- Industrial expectations [1, 16]:
  - **Horizontal** and **Vertical integration** of industrial systems and sub-systems;
  - **Flexibility**, **Real-time data analysis**, Strategic and operational decision-making, **augmented automation**.
  - End-to-end engineering, **full integration** of **PLM**
  - **Operations improving**, *lower down-times* and *higher productivity*
  - Supply Chain integration
  - Enabled tools for sustainability
- Expectations are considered reachable with the **transposition** of the industry in the **digital domain**, to manage its embedded **complexity:**
  - Project target: **simplify introduction of AI** *into the industrial system;*
  - Limitations: industrial complexity.

[1] Ghobakhloo M., Industry 4.0, digitization, and opportunities for sustainability (2020), [16] Tao F. et al., Digital twin-driven product design, manufacturing and service with big data (2018)

Industrial Technologies State of the Art

Research	First keyword group	Second keyword group	Search within results
First research	Make to Stock or MTS Make to Order or MTO Assembly to Order or ATO Engineering to Order or ETO Flow-shop Cellular Manufacturing Job-shop Project-shop	Internet of things or IoT Artificial intelligence or AI Digital Twin or DT Agent Multi Agent Systems or MAS	Competitive priorit*
Second research	Make to Stock or MTS Make to Order or MTO Assembly to Order or ATO Engineering to Order or ETO Flow-shop Cellular Manufacturing Job-shop Project-shop	Industry 4.0	Competitive priorit*

Additional filters:

- From 2015 to 2022

Results:

- 989 articles collected

Topics	Occurrences	Percent occurrence %
Scheduling	75	64.66%
Operations control	27	23.28%
Literature review/Survey	9	7.76%
Maintenance	7	6.03%
Environment	6	5.17%
Supply Chain	6	5.17%
SME	4	3.45%
Shop Floor Discovery	3	2.59%
Humans in the Loop	2	1.72%

Keyword groups:

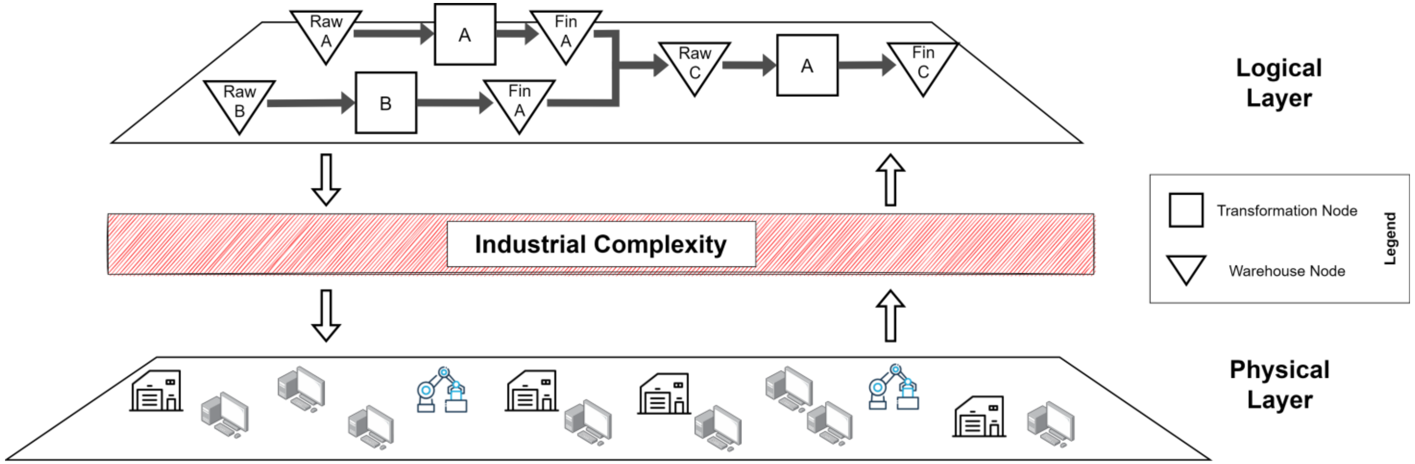
- Group 1: industrial ***physical*** architectures components
  - Layout
  - OPP - *Order Penetration Point* or CODP - *Customer Order Decoupling Point*
- Group 2: technologies for industrial ***digitalization***

Takeaways:

- Two **most researched topics** are **scheduling,** and **operations control** supported by technologies involved, i.e., **AI** and **Agents**;
- ***Interest around IoT*** *and* ***DTs is growing***;
- **Most of the scientific studies on intelligent applications are scenario-specific**.

Industrial Complexity Issues

- Industry 4.0 technologies are expected to simplify shop-floor management and mitigate the overall ***industrial complexity*** [1].
- ***Growing demand for mass customization*** pushes for more intricate industrial systems.
- Mass customization is a ***paradox*** for contemporary companies [2], which need new strategies for the next evolutive step.
- The ***complexity level*** of a production system ***increases the effort to respond to customers' requests***.
- Modelling industrial complexity is strategic to clarify ***the challenges of future industrial systems*** and ***correctly address them***.

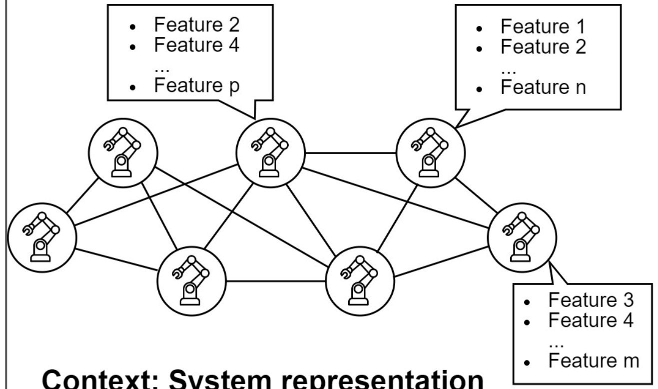


[1] Ghobakhloo M., Industry 4.0, digitization, and opportunities for sustainability (2020), [2] Rebecca Duray, Mass customization origins: Mass or custom manufacturing? (2002).

Industrial Complexity

- Industrial complexity has been studied in research [3, 4, 5].
- Complexity definitions:
  - "*something entwined*" (or an *intertwined system*)
  - "*something made of several closely connected parts*" [3].
- Industrial Complexity considers the **resulting intricateness** of *all the systems needed to fulfil the industrial production targets*.
- In the industrial domain, <u>2 types of complexity</u> are usually distinguished:
  - *static complexity*;
  - *dynamic complexity.*

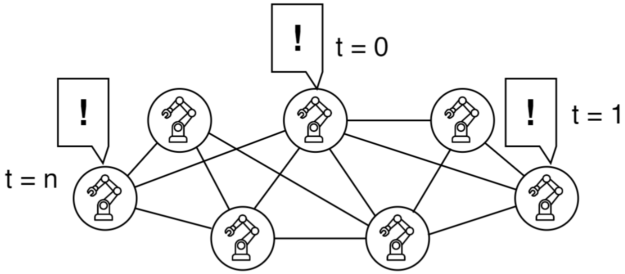
Static complexity



Context: System representation

Designed relationships?
Designed architecture?

Dynamic complexity



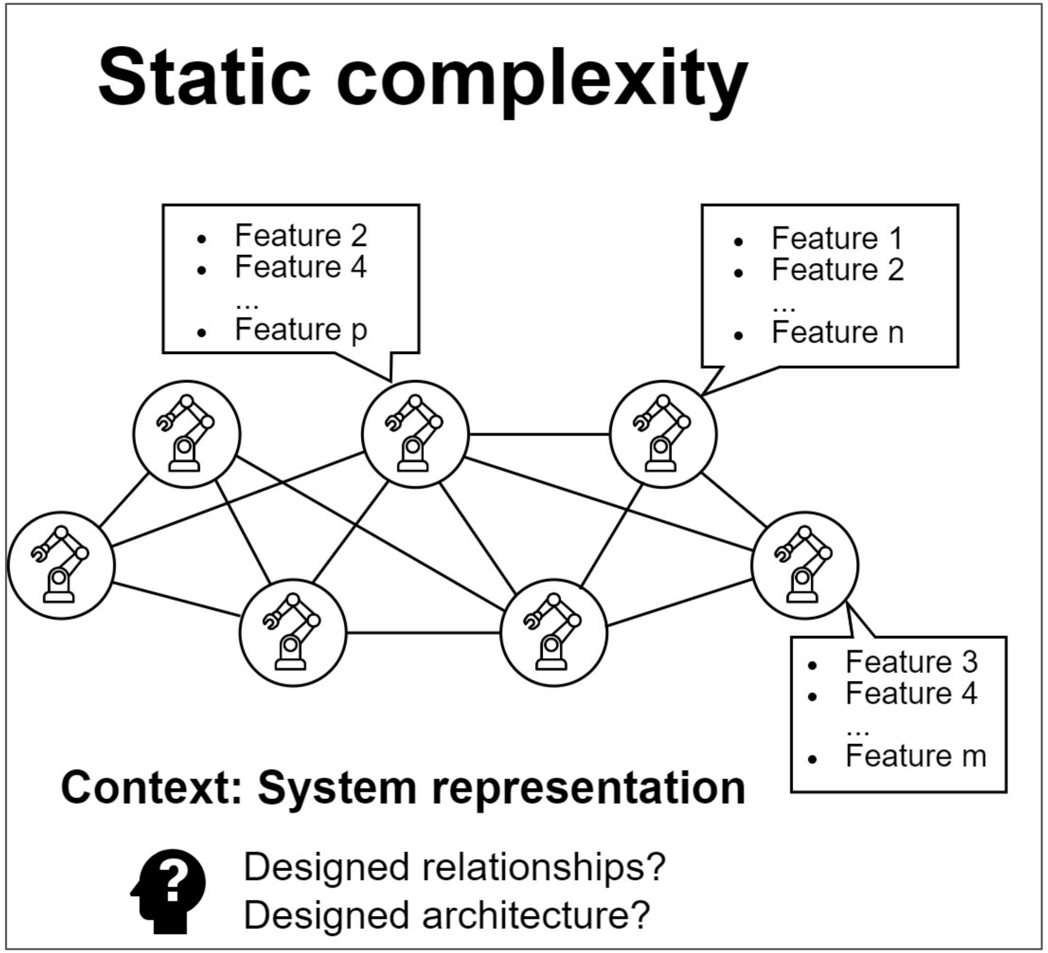
Context: System management

How should I react?
What happens if I do A or B?

[3] Monostori L. et al., Complexity in engineering design and manufacturing, [4] Modrak V. et al., Exploring the Complexity Levels of Discrete Manufacturing Processes, [5] Herrera V., Complexity in Manufacturing Systems, a literature review

Static Complexity in the Industrial Domain

- Referred to the product and production system structure in a **time-independent** manner [6].
- Considers the *amount of information necessary to describe the state of a system concerning the manufacturing tasks it needs to carry on*.
- Possible sources of static complexity are:
  - Product complexity [7, 8]
  - Product portfolio mix [6, 8]
  - Layout [6, 7, 8]
  - Equipment [6, 7, 8]
  - …
- *Takeaway*: static complexity considers the ease of describing the industrial system ***when it is turned off***.



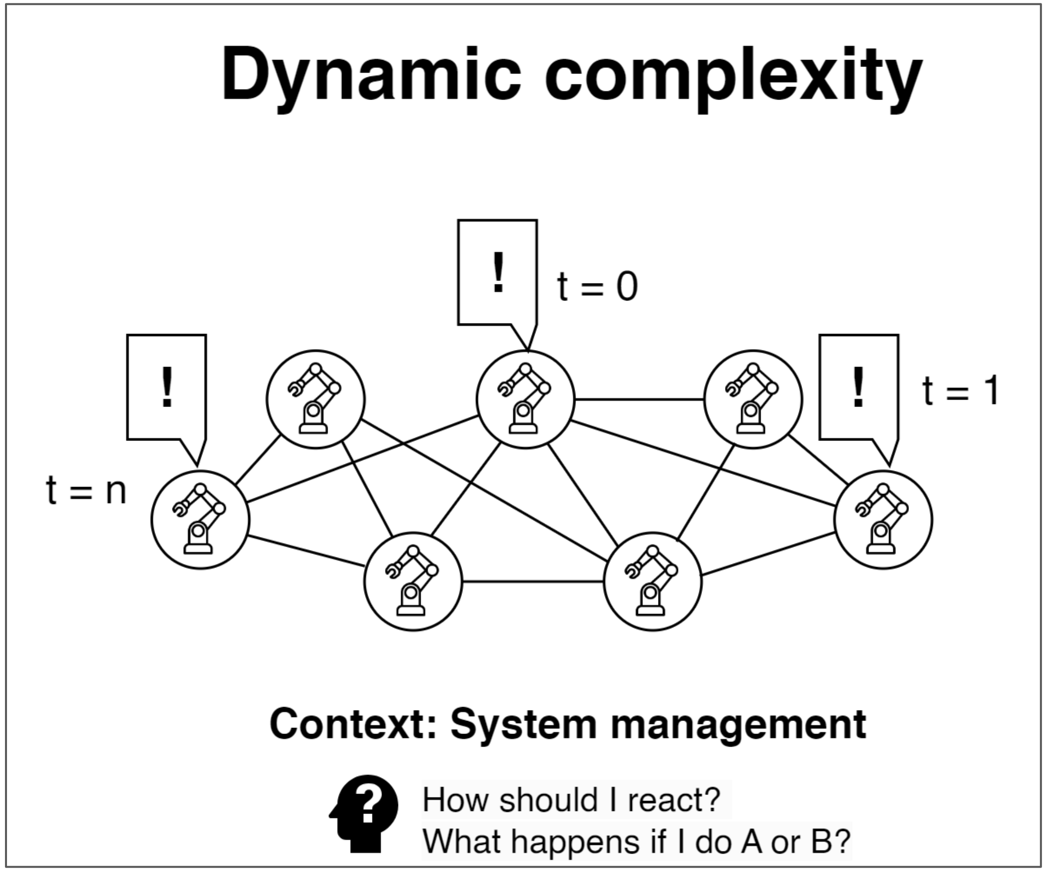
[3] Monostori L. et al., Complexity in engineering design and manufacturing, [4] Herrera V., Complexity in Manufacturing Systems, a literature review, [6] Gabriel AJ., The effect of internal static manufacturing complexity on manufacturing performance

Dynamic Complexity in the Industrial Domain

- Is defined as **time-dependent** and is also related to **real-time operations activities** [3, 4, 6].
- Considers deviations from the normal/steady-state, comprising uncertainties, unpredictable events, and adaptive responses.
- Drivers for this kind of complexity may be:
  - *Internal*:

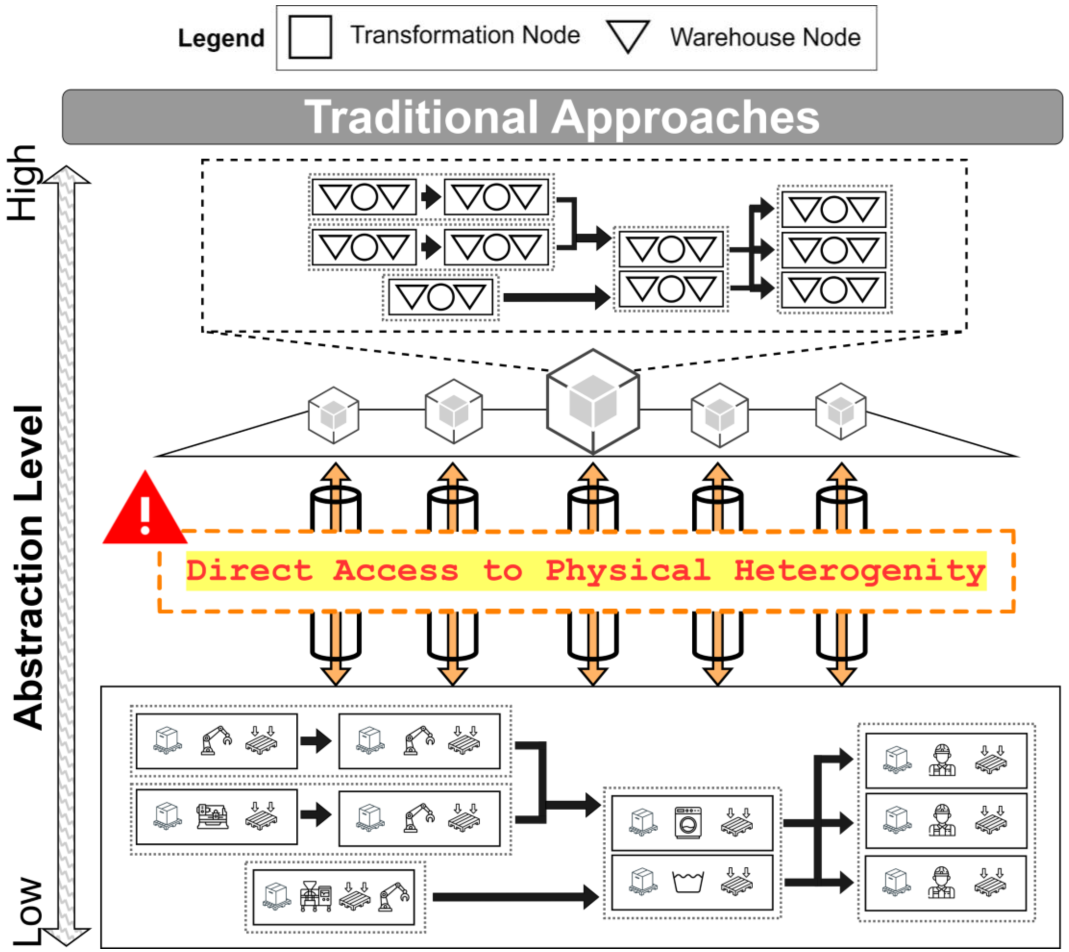
    breakdown occurrences [3, 6], maintenance policies [3, 6], scheduling activities [3, 6], quality problems [3, 6]
  - *External*:

    defects in received raw material or delays due to supplier unpredictable occurrences [3, 4].
- <u>*Takeaway*</u>: dynamic complexity considers all inconveniences and unforeseen happenings of the industrial system statically defined <u>***when it is turned on.***</u>



[3] Monostori L. et al., Complexity in engineering design and manufacturing, [4] Herrera V., Complexity in Manufacturing Systems, a literature review, [6] Gabriel AJ., The effect of internal static manufacturing complexity on manufacturing performance

Are Static and Dynamic Complexity enough?

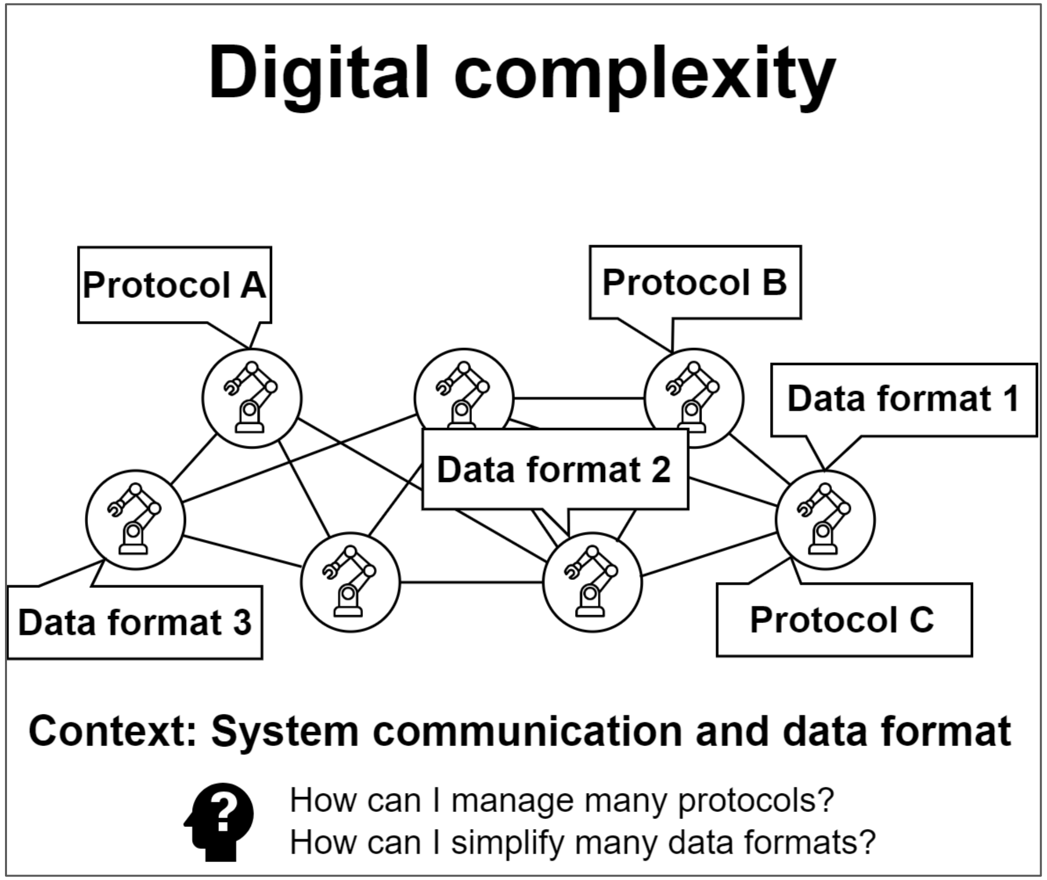


[15] Hazra A. et al., A Comprehensive Survey on Interoperability for IIoT: Taxonomy, Standards, and Future Directions (2021)

- Challenges in digitalizing the physical shop-floor:
  - **Specialized hardware** and **software** [15];
  - **Siloed solutions** and lack of uniformity [15];
  - Lack of adaptivity, collaboration and scalability [15];
    - Difficulties in **integrating new products into the mix**;
    - Difficulties in **integrating new production equipment** into existing ecosystems;
    - Difficulties in ***kaizen* activities** (i.e., continuous improvement) of operations;
- Actual state: **Low *abstraction*** and ***representiveness***:
  - **Direct access of applications to physical complexity** in terms of its *static* and *dynamic* nature
- Results:
  - High costs for *integration* and *maintenance*
  - *Low degree of scalability* and *personalization* of the system
  - **Lost opportunities** in terms of production management, and representation, optimization.

Digital Complexity in the Industrial Domain

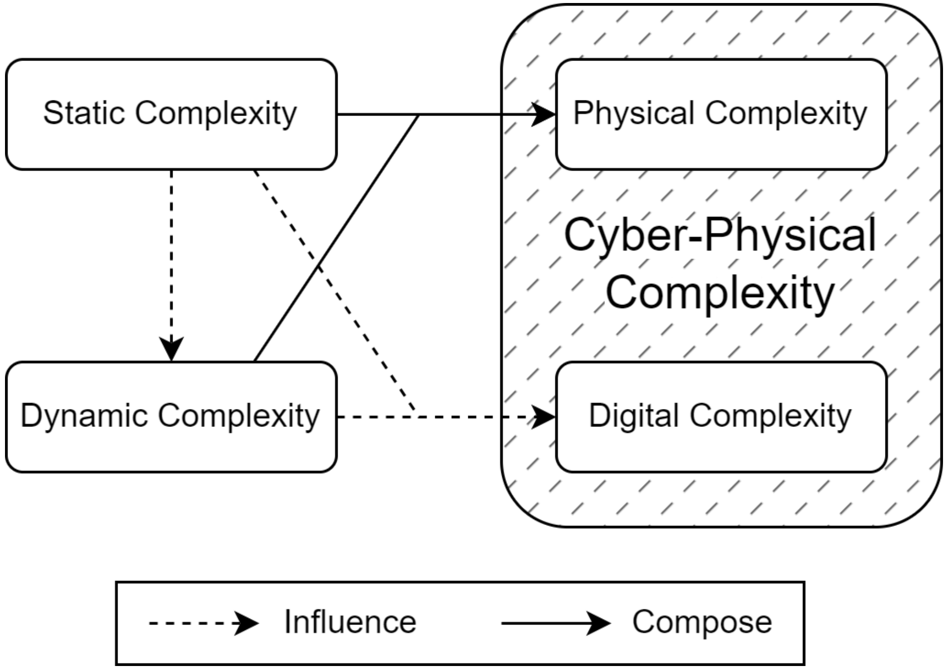
- Digital instruments are expected to bring benefits in managing static and dynamic complexity but *at the cost of a new type of complexity*: **Digital Complexity.**
- Digital Complexity deals with **challenges** in transposing the physical domain into the digital one:
  - ***Abstracting*** and ***decoupling*** heterogeneous physical entities;
  - Promoting their ***integration*** with respect the *needs of each scenario*;
  - Promoting IoT ***scalability***, ***collaboration*** and ***adaptivity*** across heterogeneous equipment;
  - ***Reflecting the physical world complexity***, i.e., the complex aspects of the physical domain that need digital representation;
  - ***Simplifying interactions with applications***;
  - Introducing ***intelligence functionalities***.



Industrial Cyber-Physical Complexity

- **Static complexity** *influences* **dynamic complexity**:
  - The higher the static complexity, the more the system is prone to uncertainties and critical events.
- **Static complexity** *influences* **digital complexity**:
  - The higher the static complexity, the higher the probability of heterogeneous equipment, products and associated processes.
- **Dynamic complexity** *influences* **digital complexity**:
  - The higher the static complexity, the higher the events to catch, model, manage, and predict, and the higher the effort for managing the heterogeneity and uniformity.

Static and *dynamic complexity* compose the industrial ***physical complexity***. The *physical* and *digital complexity* compose the industrial ***Cyber-Physical Complexity***.



Handling Industrial Complexity

- There are 3 ways to deal with complexity: **avoid it**, **minimize it**, and **manage it** [3]. Industry 4.0 acts toward the *second* and the *third option*.
- How to manage and eventually abstract the complexity of the physical world captured by the IoT? Using ***Digital Twins***.
- There is still a gap between applications needs and the complexity brought by IoT.
- **Digital Twins** have been widely recognized as the **steppingstone for industrial environments** towards Industry 4.0 [7, 8], and the **consequent application of Artificial Intelligence** on the shop-floor [8].

[3] Monostori L. et al., Complexity in engineering design and manufacturing
[7] Cheng j. et al., DT-II:Digital twin enhanced Industrial Internet reference framework towards smart manufacturing (2020),
[8] Jan Z. et al., Artificial intelligence for industry 4.0: Systematic review of applications, challenges, and opportunities (2023),

Digital Twins for Cyber-Physical Complexity

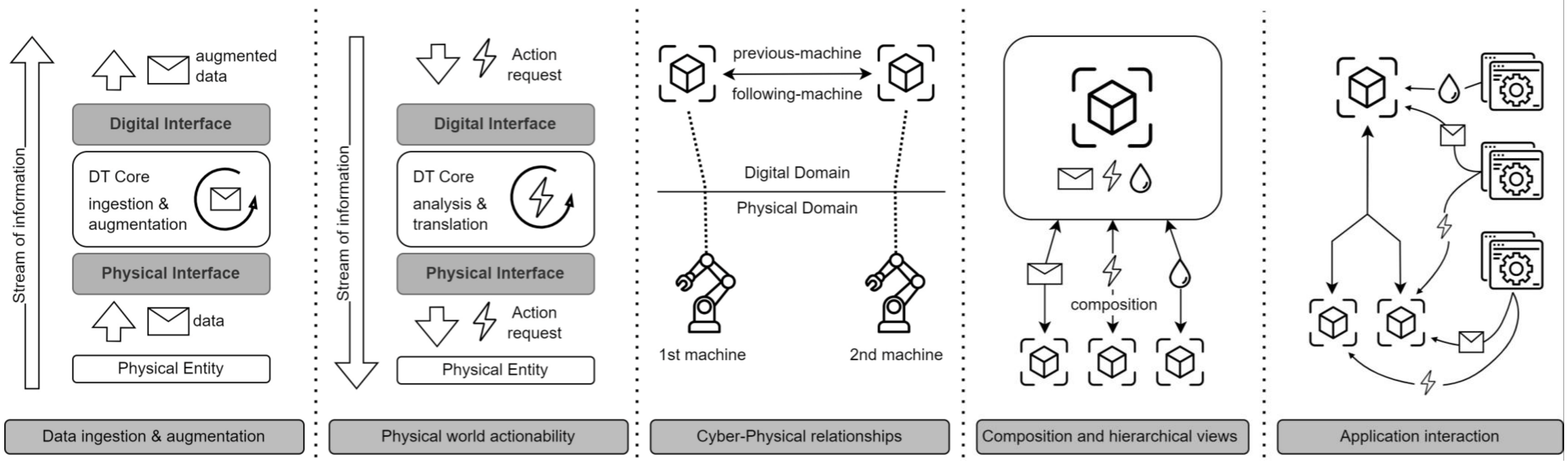
- The definition and purpose of DTs are different across research areas [10, 11, 12, 13]

- “A **Digital Twin (DT)** is a **comprehensive software representation** of an individual **physical object**. It includes **properties**, **conditions**, and **behavior(s)** of the real-life object **through models and data**. A Digital Twin is **a set of realistic models** that can **simulate an object’s behavior** in the **deployed environment**. The Digital Twin **represents** and **reflects** its physical twin and remains its virtual counterpart **across the object’s entire lifecycle** [9].

[9] S. Haag, and R. Anderl. "Digital Twin–Proof of concept." Manufacturing Letters 15 (2018)
[10] Minerva R. et al., Digital Twin in the IoT Context: A Survey on Technical Features, Scenarios, and Architectural Models (2020)
[11] Kaklis D. et al., Enabling digital twins in the maritime sector through the lens of AI and industry 4.0 (2023)
[12] Wang W. et al., A proactive material handling method for CPS enabled shop-floor (2020)
[13] Friedrich J. et al., A framework for data-driven digital twins for smart manufacturing (2022)

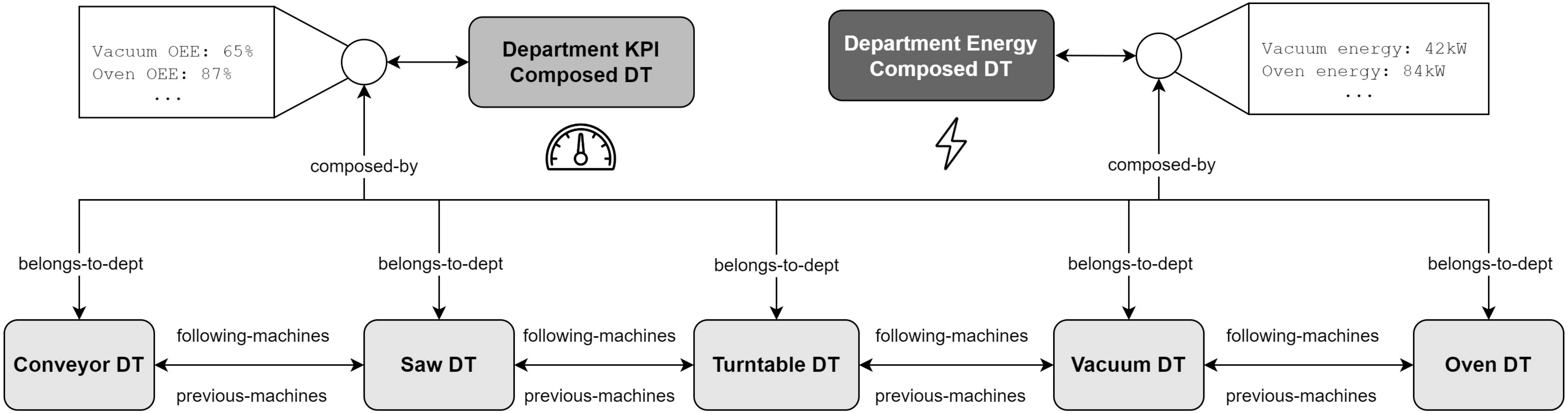
Digital Twins in the Industrial Domain

- **Integrate different physical protocols** and expose the most suitable with respect to the modelled scenario;
- **Select useful information** to reflect in the digital domain with respect to the given use case and logically order it;
- **Offer a common entry point for actions** towards the physical domain;
- **Model existing relationships** among physical assets and higher-level concepts they are part of;
- **Compose heterogeneous physical assets** to obtain a cohesive logical entity;
- **Ensure a consistent point of interaction** with industrial applications.



Digital Twins in the Industrial Domain

- ***Relationships*** and ***Composability*** are very useful features to abstract and model industrial domains.
- They enable the opportunity to represent upper-level ***Physical Concepts*** starting *from underlying physical assets*.

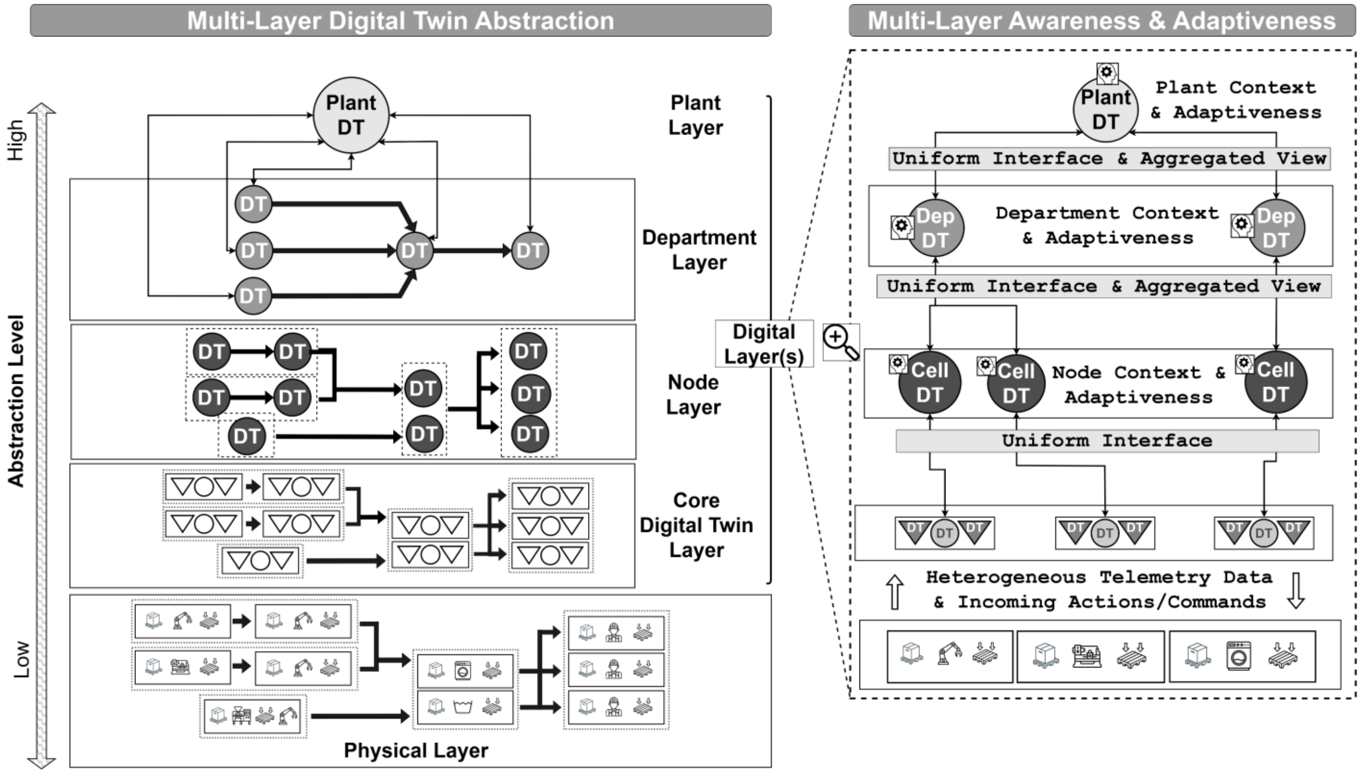


DTs in Industry: Envisioned Result

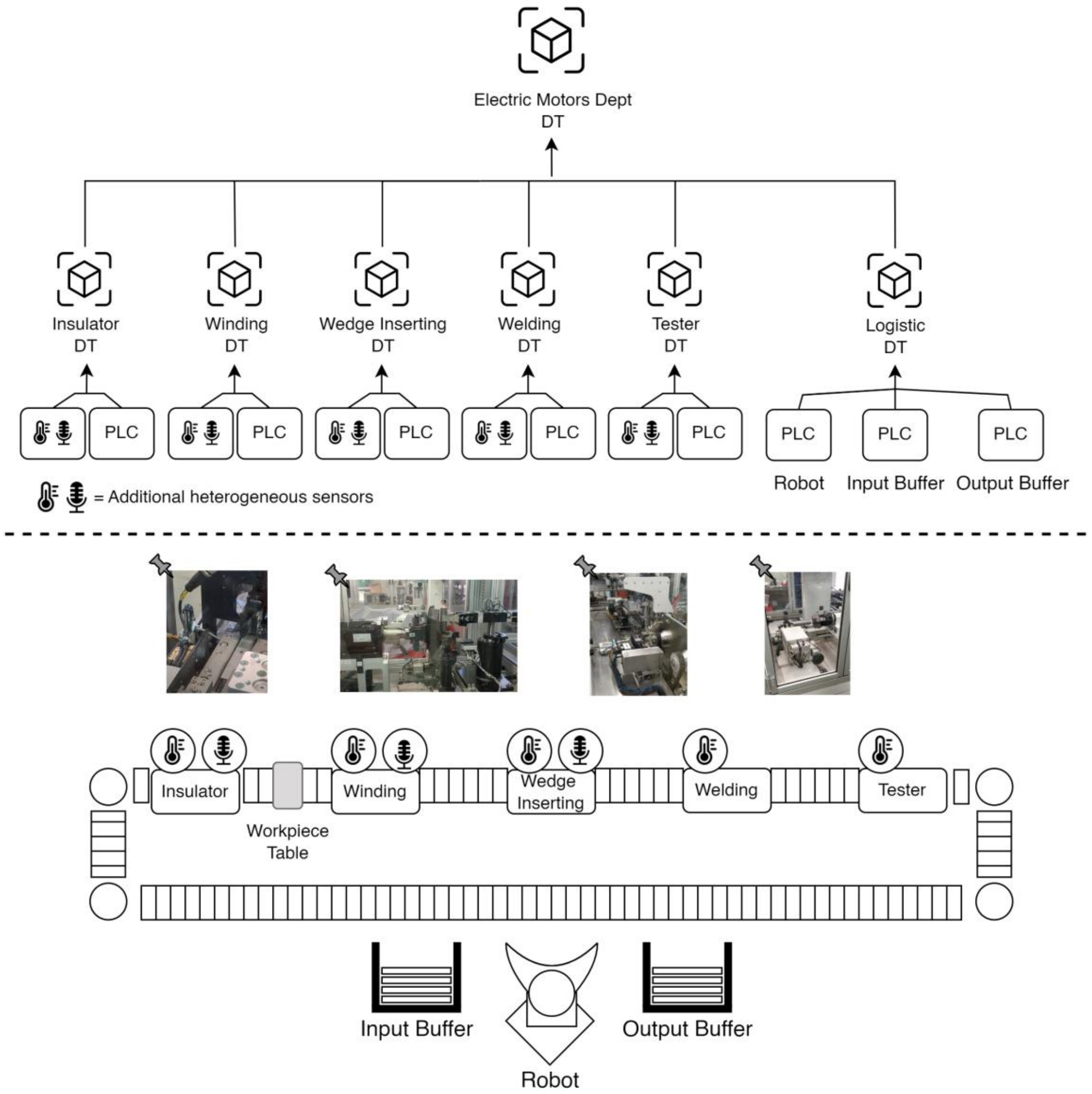
- The digitalized industry of the future will have the whole ***Physical Concepts pyramid*** transposed in the digital domain and offered to upper-level applications:
    - Physical equipment composes a ***Production Node***;
    - ***Production Nodes*** compose a ***Department***;
    - ***Departments*** compose a ***Plant***.

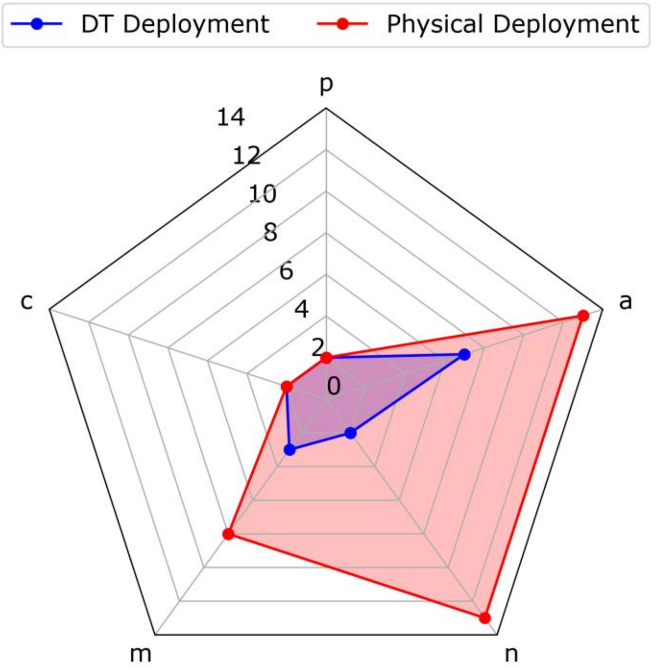
- *Horizontal* and *vertical relationships* among adopted equipment will be described by DTs, enabling *navigability* of the physical system.

- The result is the representation of the adopted ***industrial architecture***.



Digital Complexity Index: a Real Case Scenario



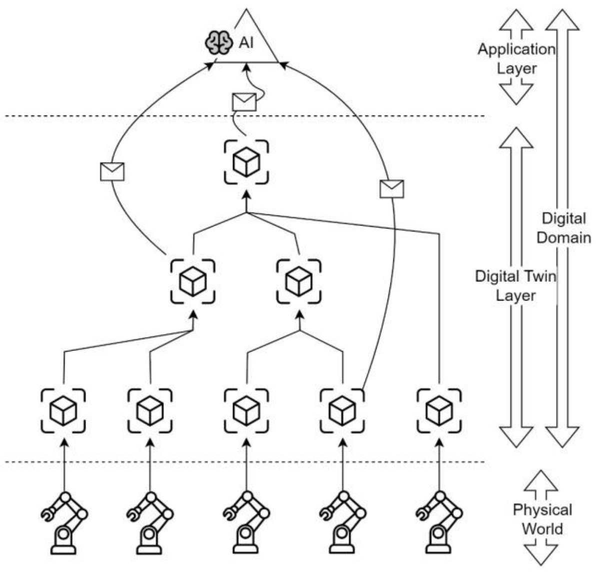


$$\boldsymbol{DCI} = \sum_{i=1}^{5} criterion_i \times IF_i$$

Criterion	Imp. Factor	Use Case without DT	Use Case with DT
Required Protocols (p)	2	2	2
Communication Patterns (c)	1	2	2
Data Formats (m)	3	8	3
Interaction Points (n)	2	13	2
Aggregation Points (a)	3	13	7
DCI	–	95	40

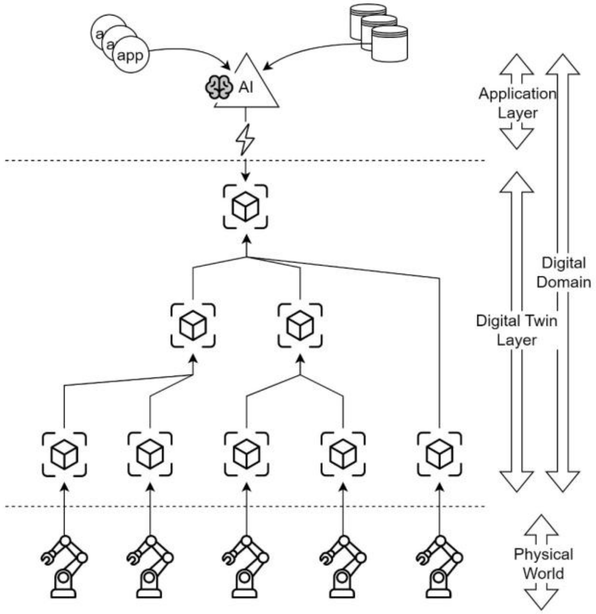
DT & AI Industry: where to put AI?

AI analysing provided DTs information, exposing insights



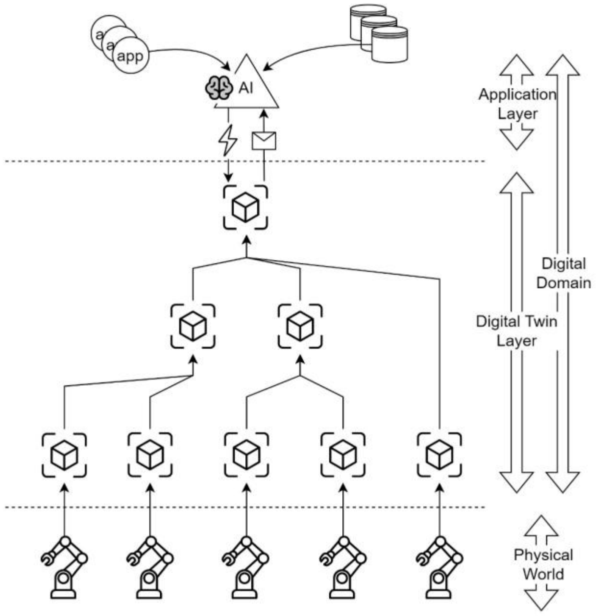
Observer AI

AI receiving information from external sources and actioning exposed DTs



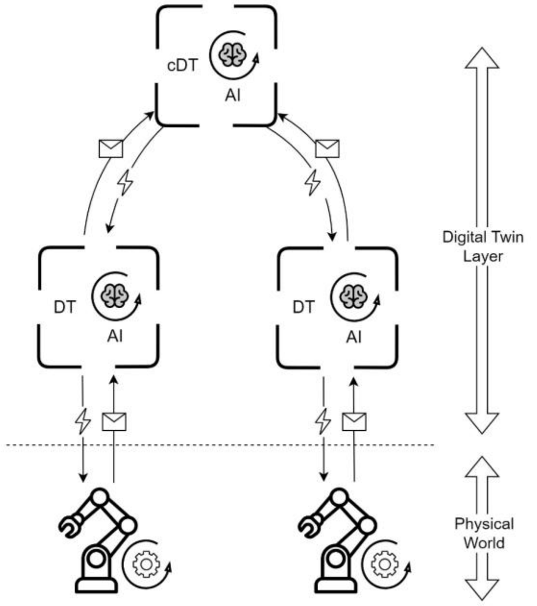
Advisor AI

AI modifying the DT behaviour based on DT and external data
Production modularity example



Controller AI

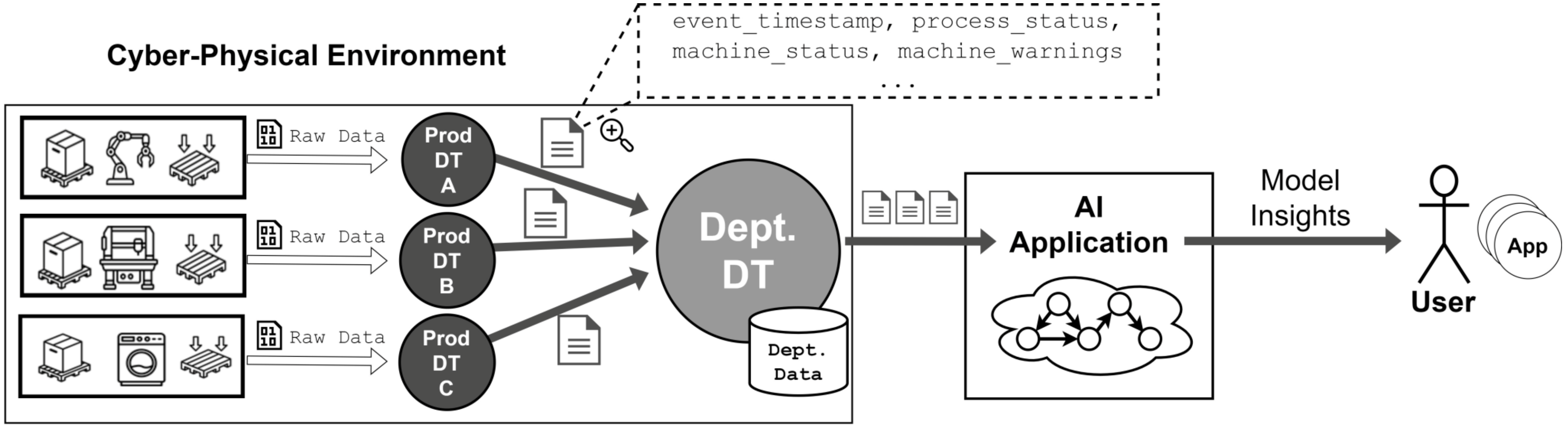
AI otpimising internal DT behaviour based on its internal data
Energy opt example



Embedded AI

AI & DT interaction – Observer AI

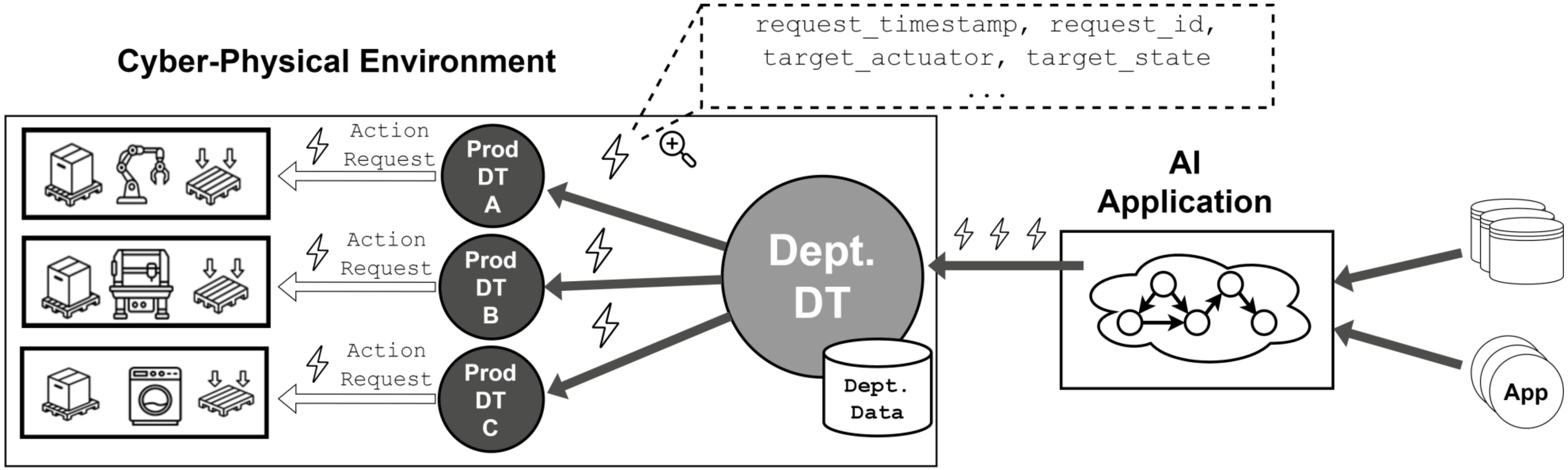
- AI external to an industrial DT ecosystem;
- Receives data from DTs of its interest;
- Monitors single DTs or their compositions;
- Does not know anything about the internal structure of each DT;
- For advanced monitoring of single DTs states, their compositions, or specific groups of DTs for stakeholders or applications.



[14] Crespi N. et al., Digital Twins: Properties, Software Frameworks, and Application Scenarios (2021)

AI & DT interaction – Advisor AI

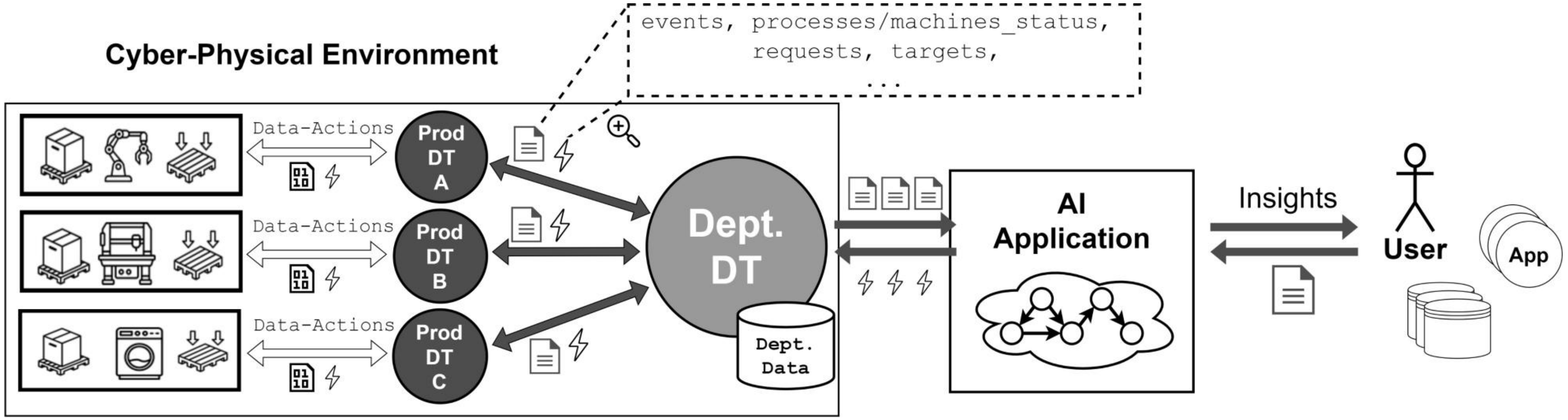
- AI external to an industrial DT ecosystem,
- Collects data from external sources;
- Does not know anything about DTs internal structure;
- Eventually requests actions to the DT ecosystem to reach a target state-of-affairs.
- For external data sources monitoring through AI and sending actions requests to adapt to the external predicted future.



[14] Crespi N. et al., Digital Twins: Properties, Software Frameworks, and Application Scenarios (2021)

AI & DT interaction – Controller AI

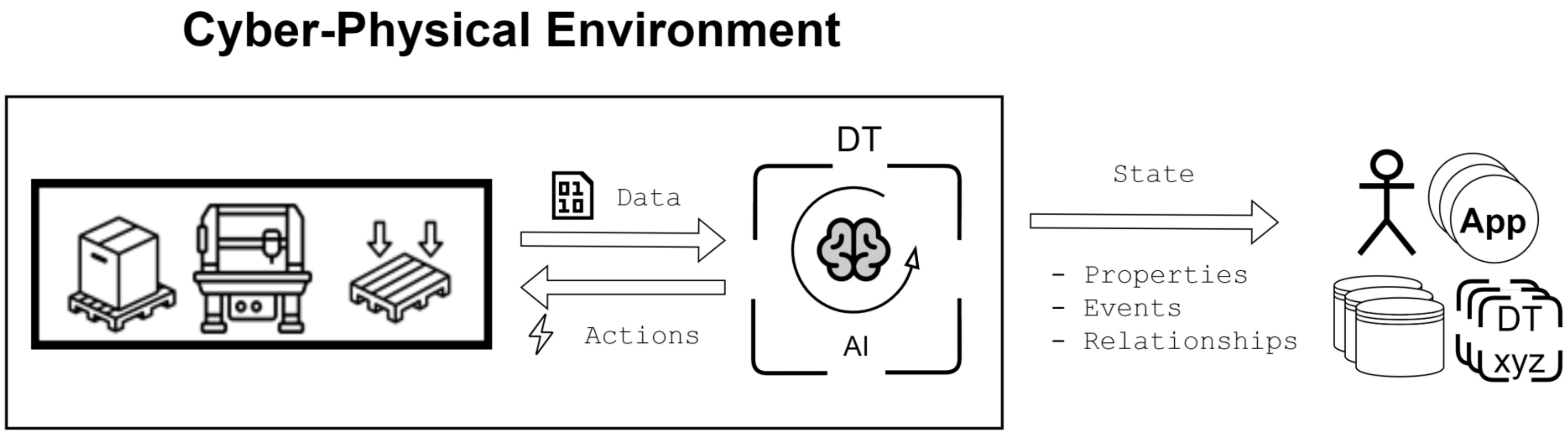
- Is a mix between *Observer* and *Advisor AI*;
- AI system external to the DT ecosystem;
- Does not know anything about DTs internal structure;
- Collects data both from the DT ecosystem itself and from external sources;
- Requests actions to DTs.
- For guiding the behavior of the DT ecosystem through external AI considering its state and external data sources, such as stakeholders, applications or databases.



[14] Crespi N. et al., Digital Twins: Properties, Software Frameworks, and Application Scenarios (2021)

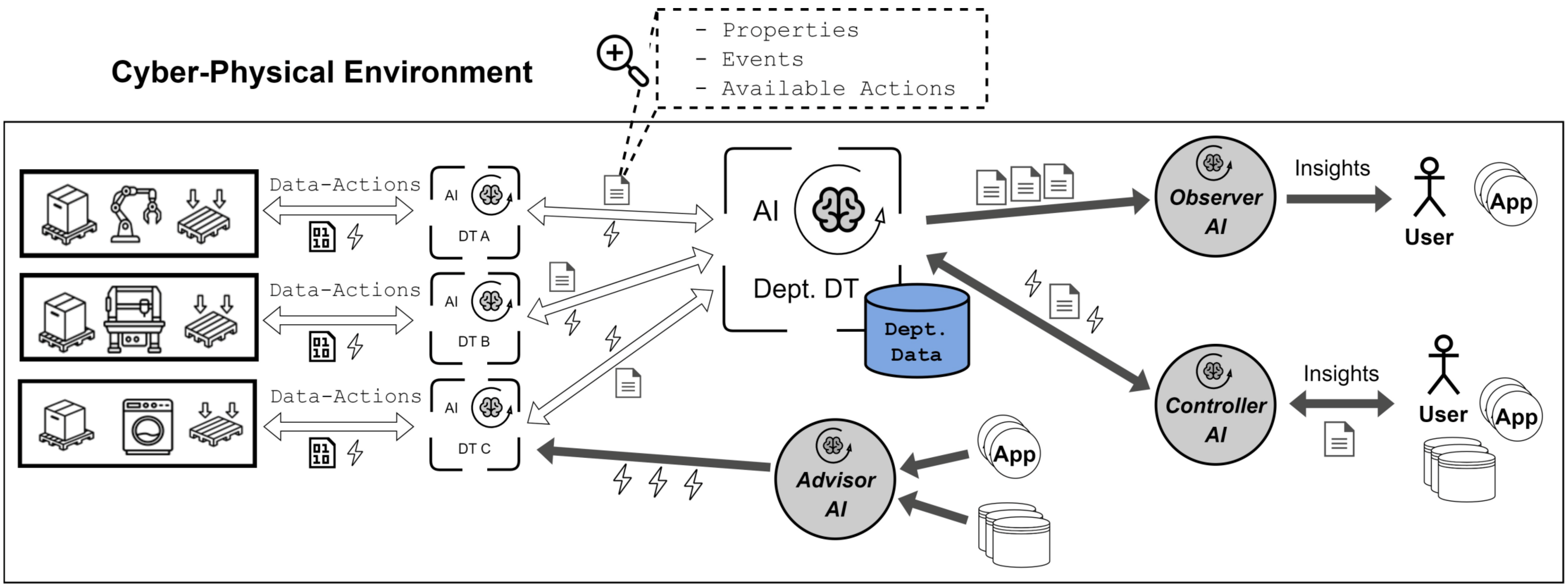
AI & DT interaction – Embedded AI

- AI internal to single DTs;
- Knows the internal structure of its DT;
- Receives data from associated resources, augments it and eventually triggers actions back.
- For internal DT inbound data augmentation through AI, and eventual actions triggering towards to obtain a desired outcome.



[14] Crespi N. et al., Digital Twins: Properties, Software Frameworks, and Application Scenarios (2021)

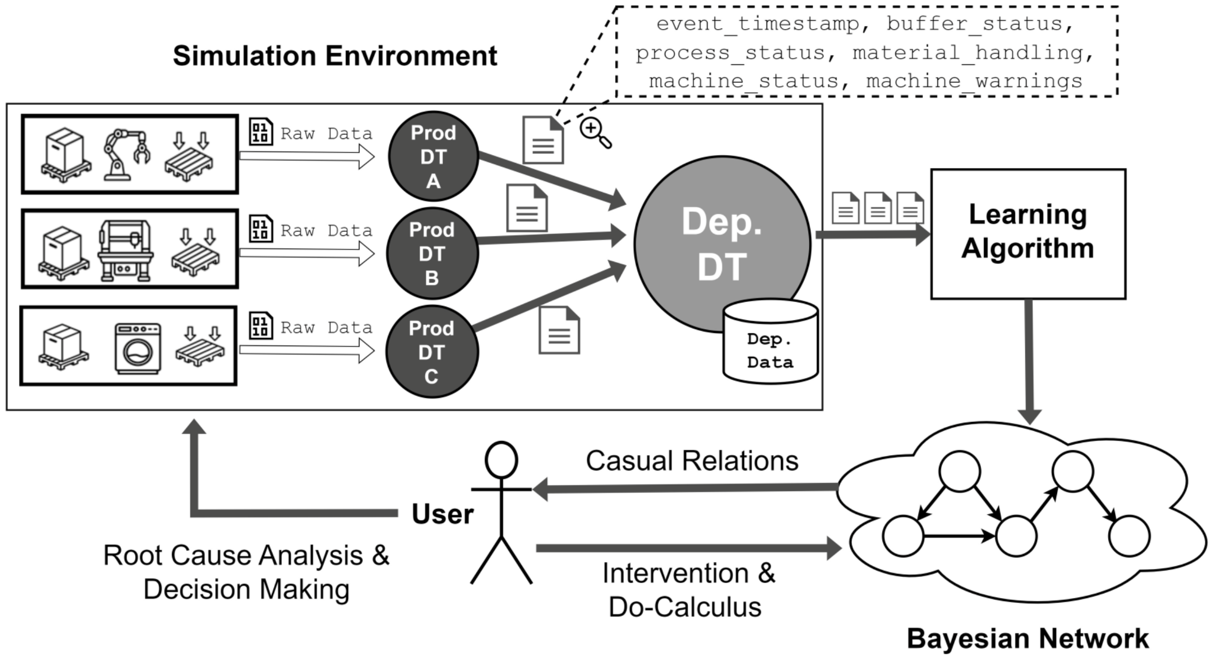
Intelligent DT Ecosystem in Industry



AI & DT interaction – Experimenting Observer AI

Target:

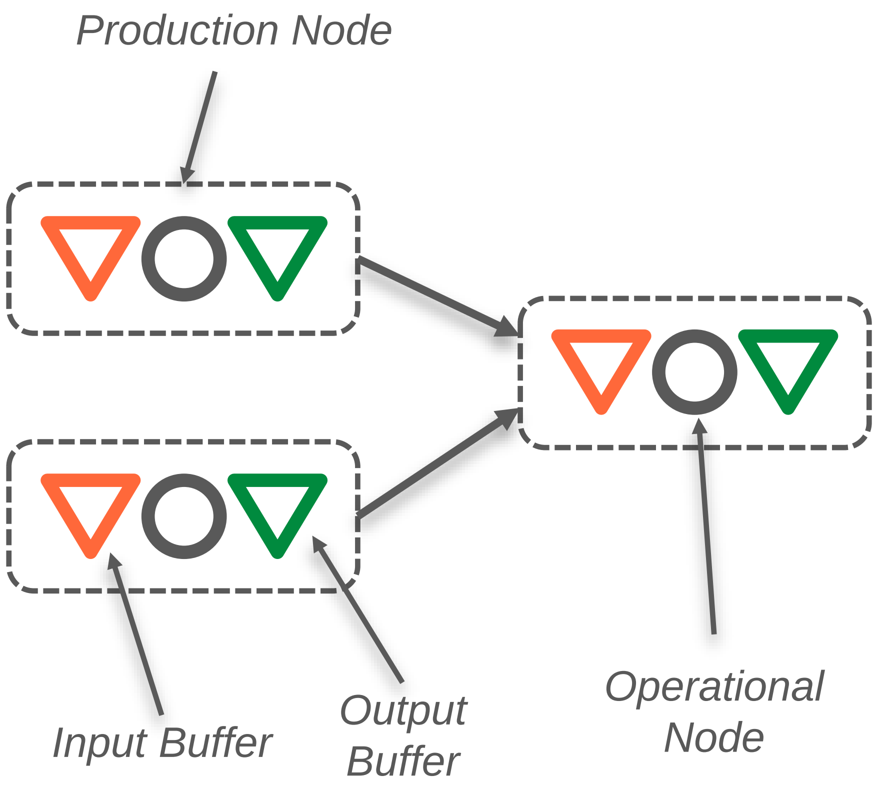
- To **practically explore the Observer AI** pattern;
- Leverage Observer AI to integrate *causality learning* in the system.



AI & DT interaction – Experimenting Observer AI

Design:

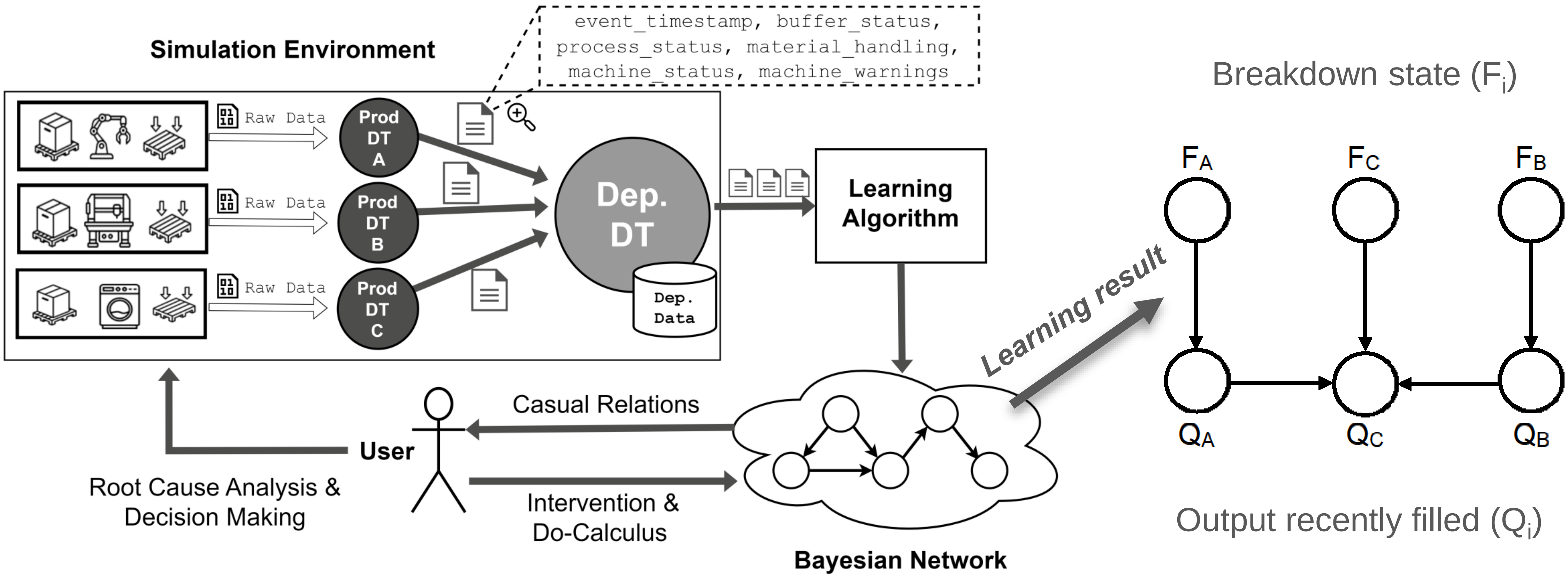
- SimPy[1] simulation of production, including machine breakdowns (stochastically modelled);
- 36 working days simulated on a single work shift;
- Downstream node produces if and only if both input pieces from upstream nodes are available;
- Monitoring if an output buffer of a production node has recently received a least one piece.



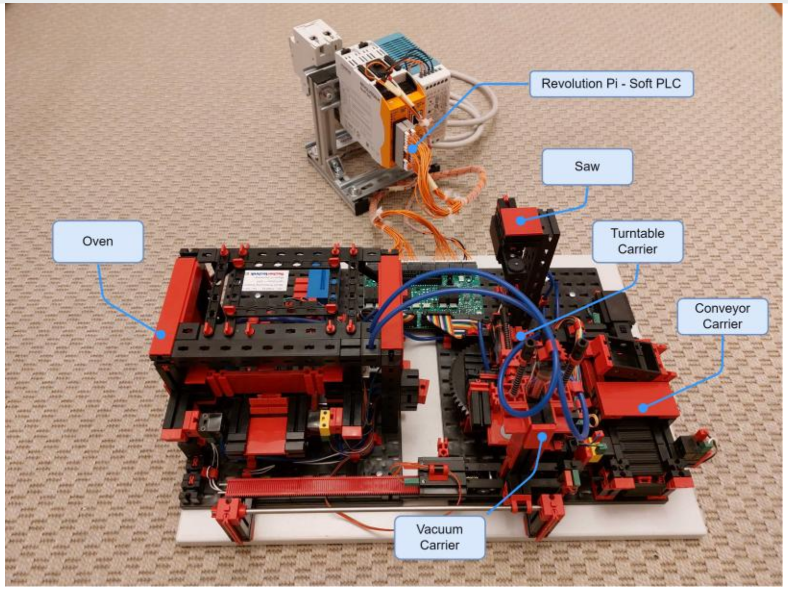
[1] SimPy docs available at: https://simpy.readthedocs.io/en/latest/

I-TH MACHINE TABLE					
Timestamp	Input buffer level	Output buffer level	Pieces produced	Breakdown state (F_i)	Output recently filled (Q_i)

AI & DT interaction – Experimenting Observer AI

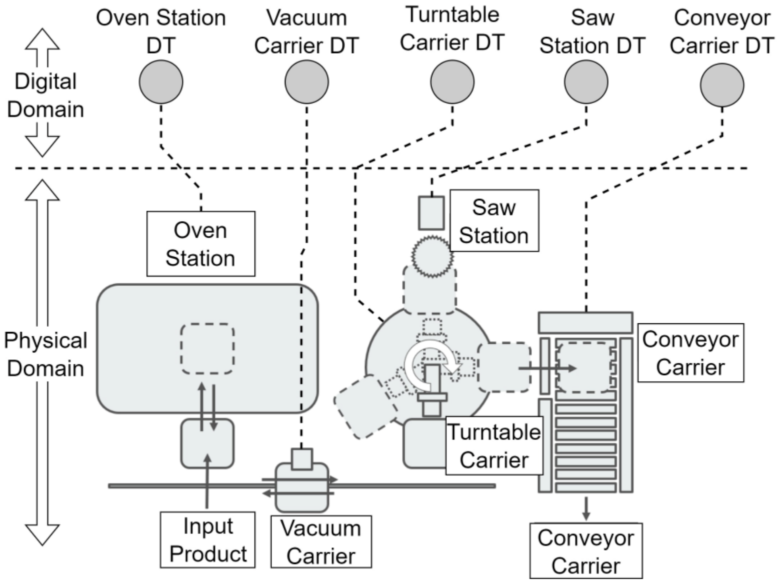


AI & DT interaction – Experimenting Advisor AI



Target:

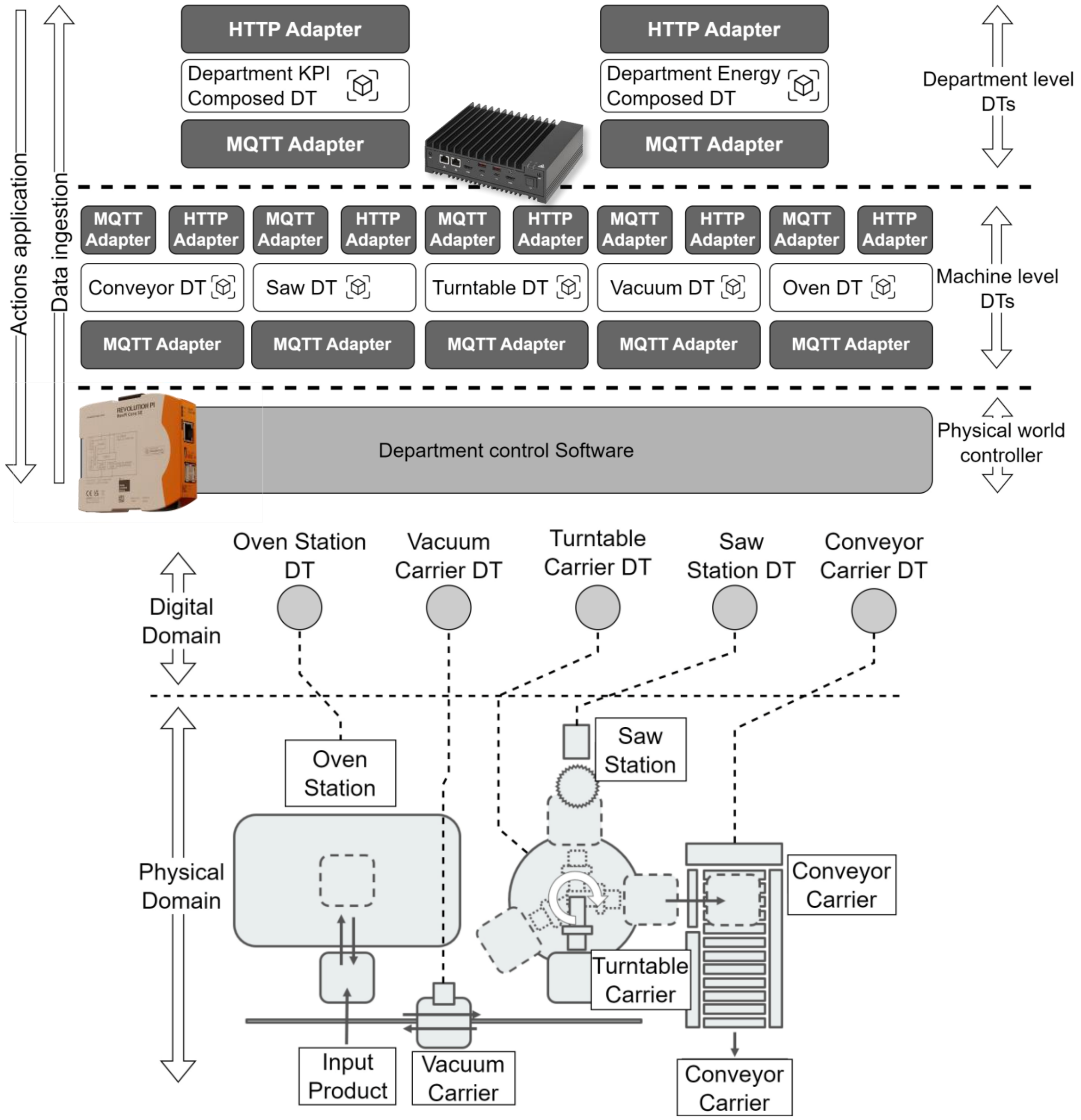
- To **practically explore the Advisor AI** pattern;
- To build a **DT ecosystem on top of a realistic physical industrial environment** (*Fischertechnik*);
- Implemented in Java using ***WLDT***;
- **Leverage *system navigability* through DT hierarchies** and **relationships** to extract valuable information from physical assets;
- Compute DT ecosystem **resources consumption.**



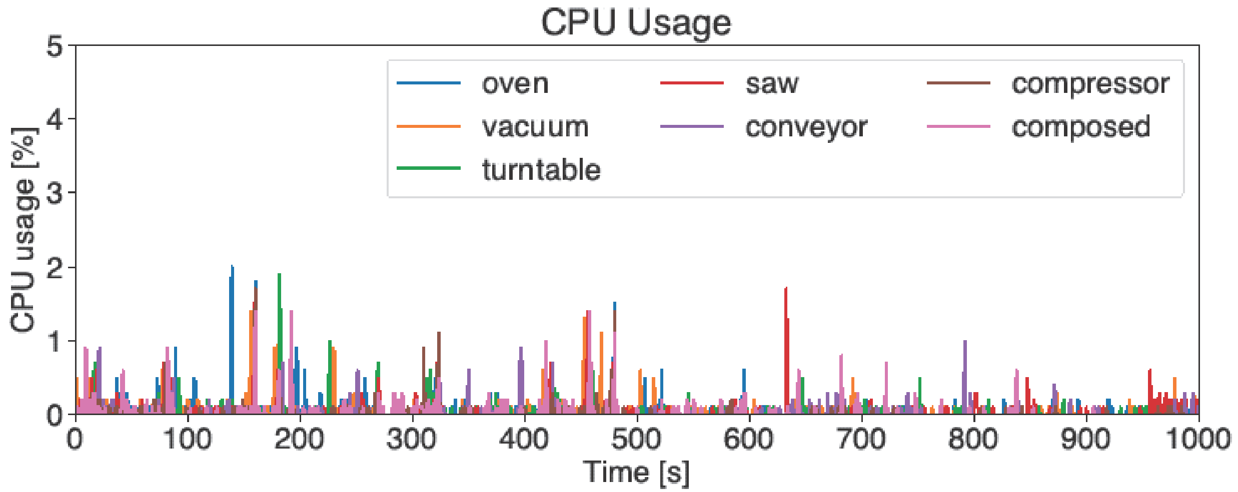
AI & DT interaction – Experimenting Advisor AI

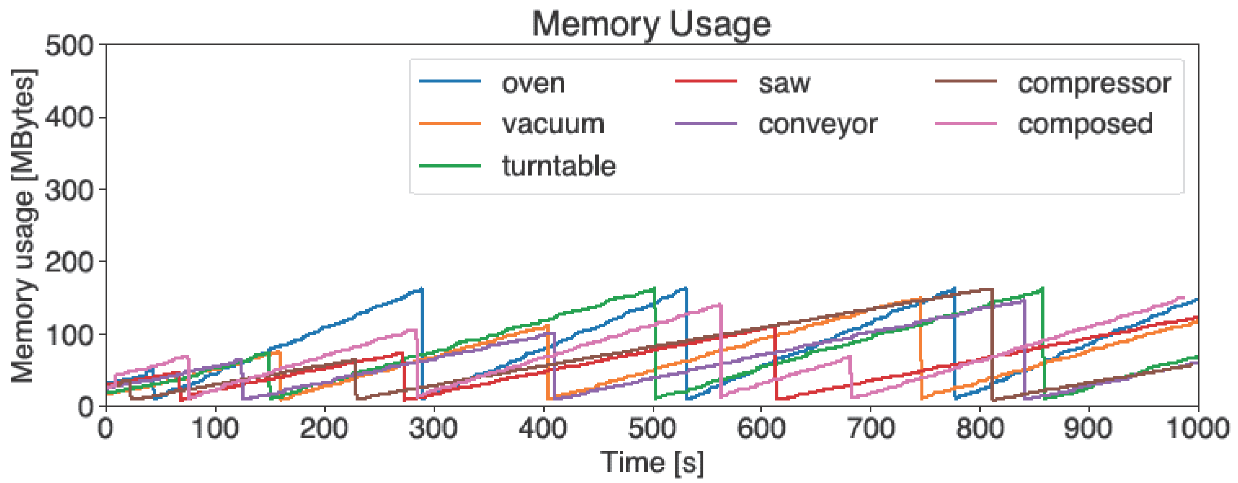
Design:

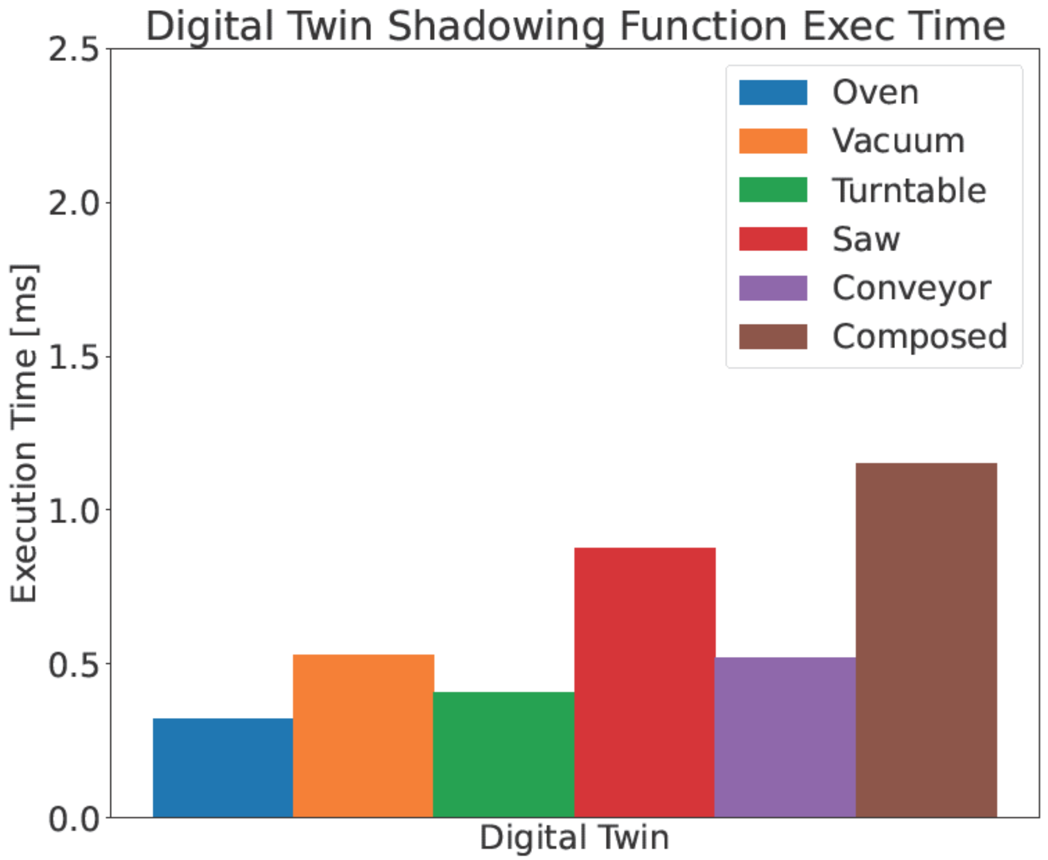
- Fischertechnik research equipment representing a 4-machines production line;
  - 2 states sensors;
  - 2 and 3 states actuators;
- Soft-PLC controlling the Fischertechnik;
- MQTT broker;
- Soft-PLC software publishes system data and reads actions-requests from the broker;
- 5 active DTs forming the Machine Layer DTs with ***WLDT***;
- 2 active DTs compositions with ***WLDT***:
  - one specialized for production KPI tracking;
  - the other specialized for energy tracking;
- DTs can control their physical counterparts;
- On top of the system, the Advisor AI interacts with the DT Ecosystem.



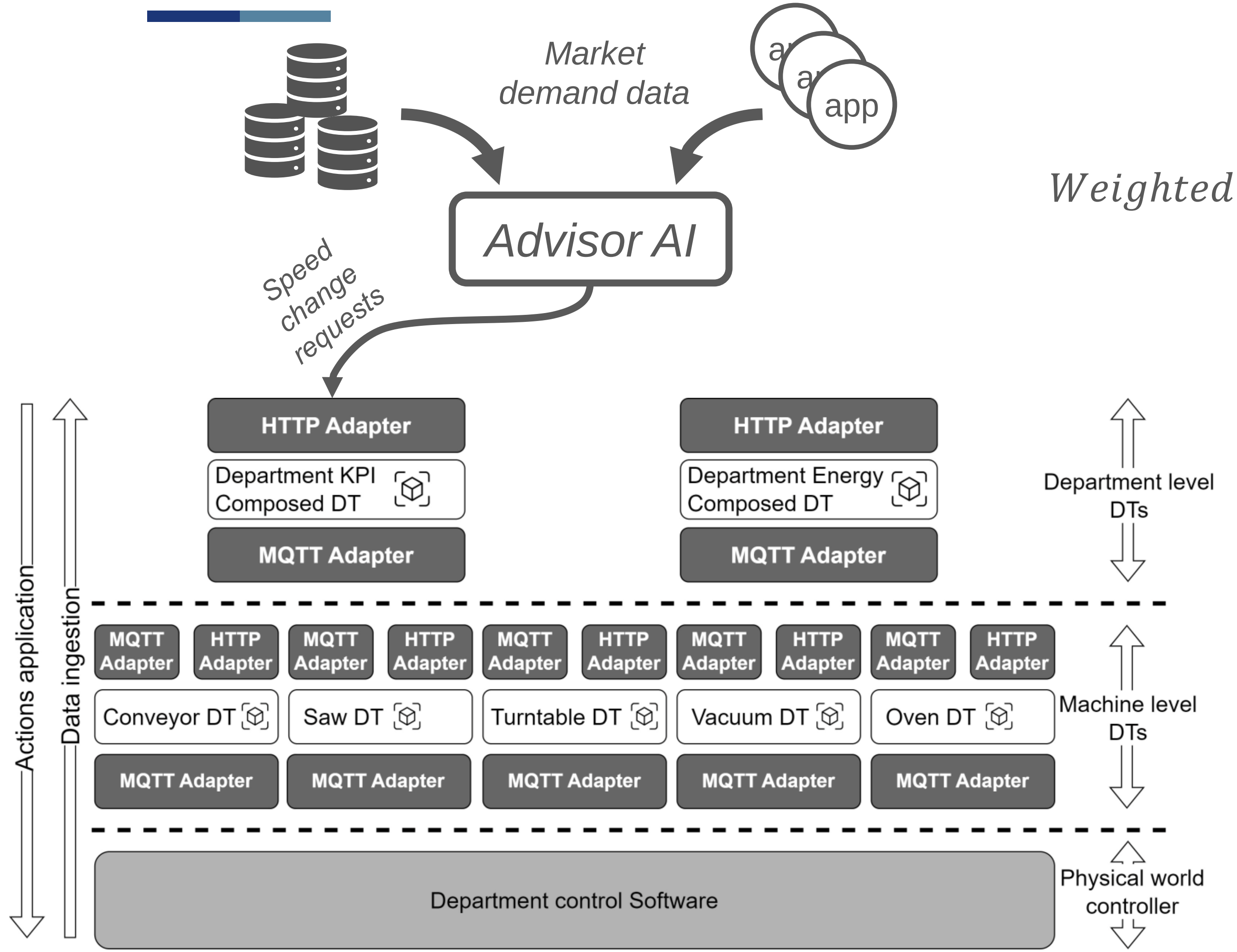
AI & DT interaction – Experimenting Advisor AI



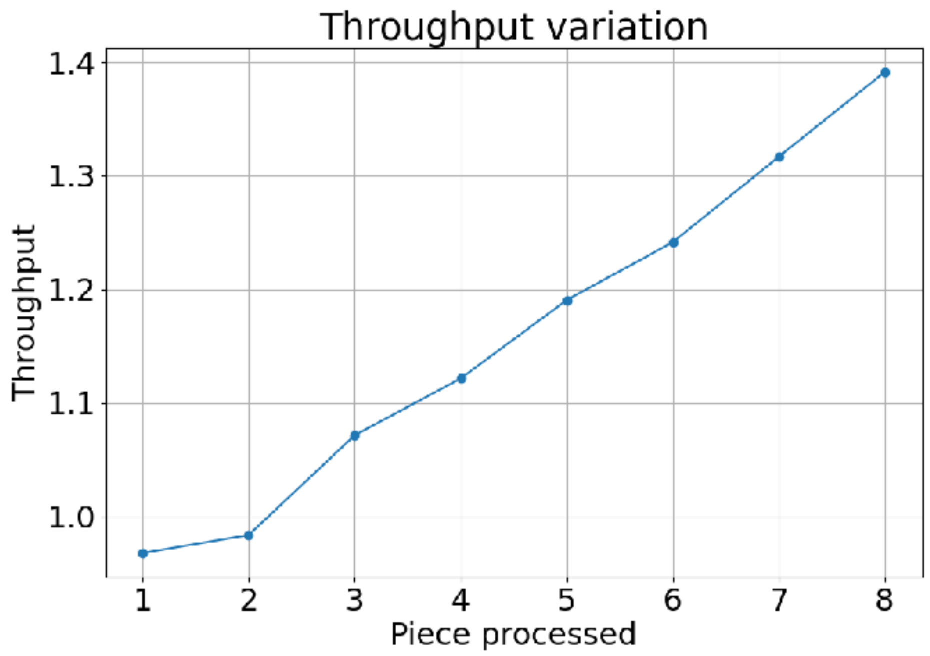




AI & DT interaction – Experimenting Advisor AI



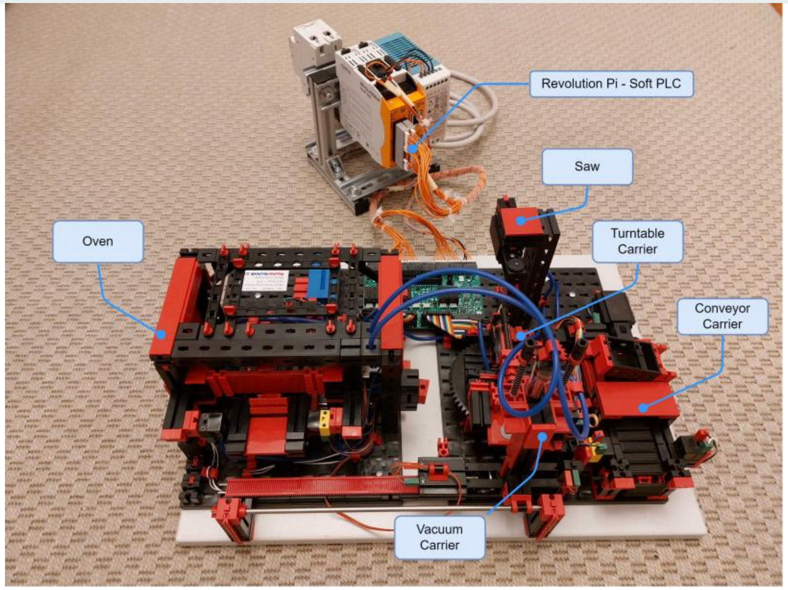
$$Weighted\ OEE = \sum_{i=1}^{n} OEE_i \times \frac{net\ available\ time_i}{total\ net\ available\ time}$$

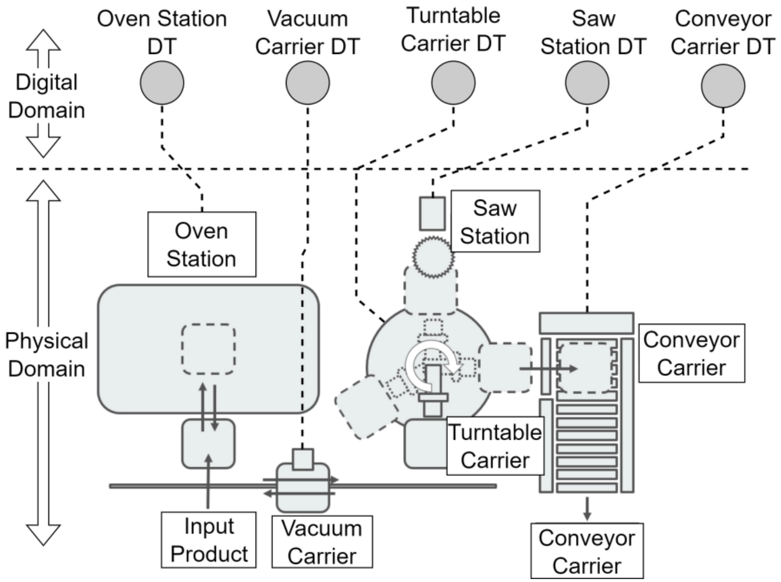


AI & DT interaction – Experimenting Embedded AI

Target:

- **Integrate an Embedded AI** pattern inside of a target DT of the **realistic physical industrial environment** (*Fischertechnik*);
- Test *data augmentation* for target DT through Embedded AI;
- Implement **physical assets coordination based on the DT ecosystem** with Embedded AI in the loop.

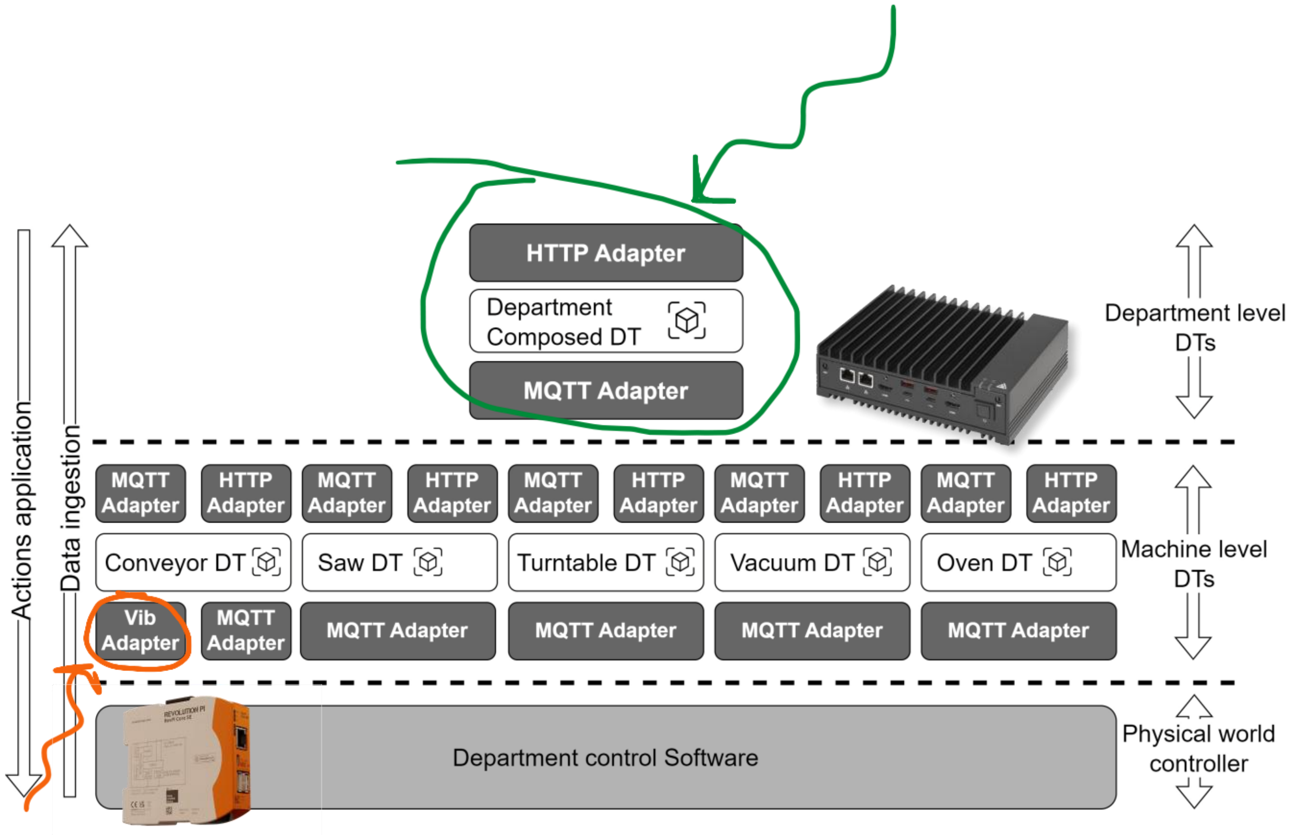




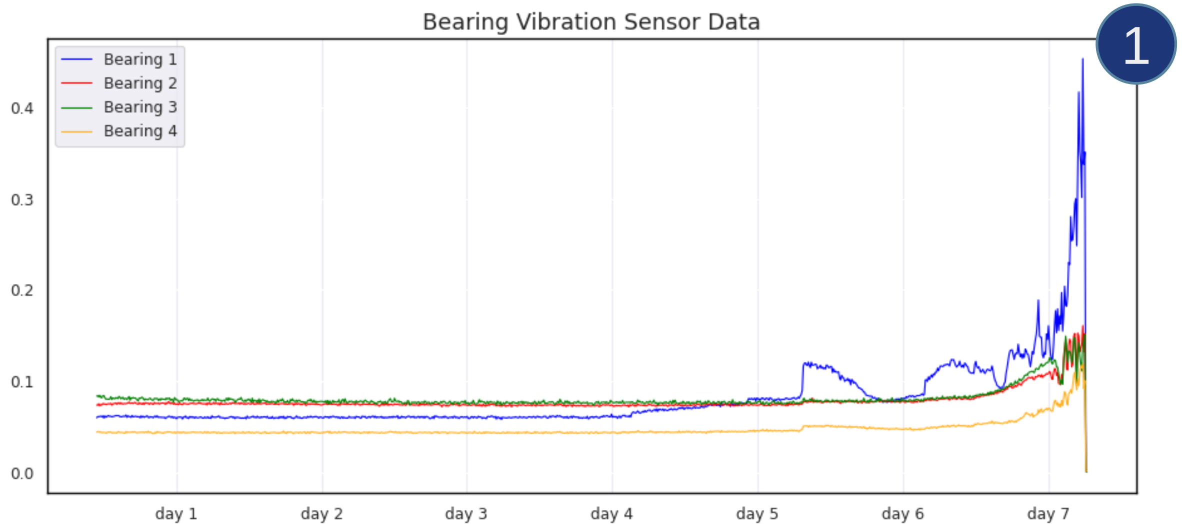
AI & DT interaction – Experimenting Embedded AI

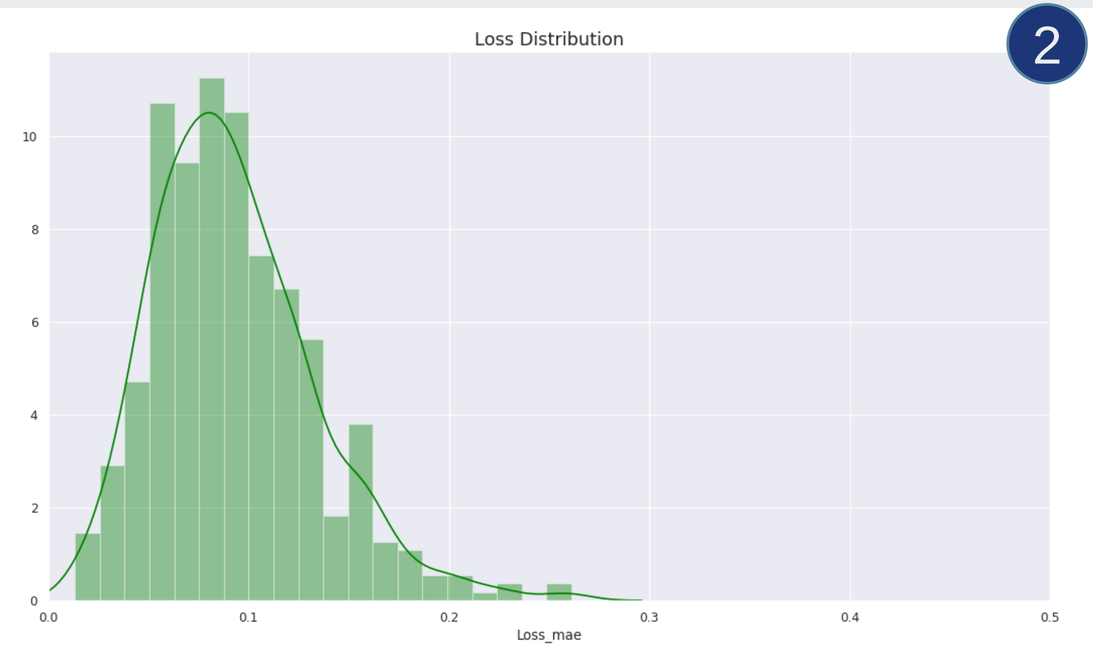
Design:

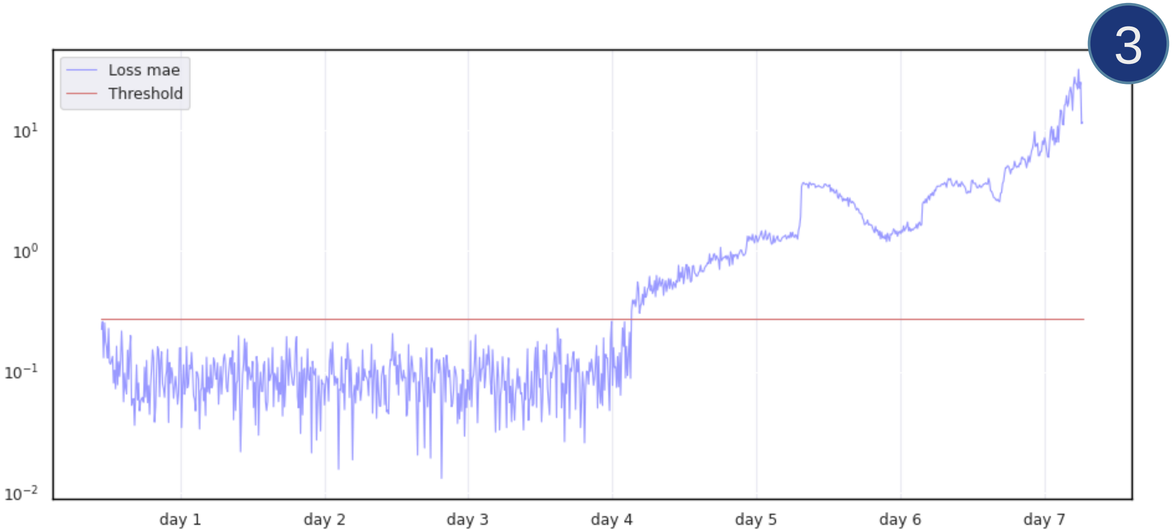
- Fischertechnik testbed based;
- One department composition;
- Conveyor having a Vibrational Physical Adapter **simulating a *vibrational sensor*;**
    - Simulation obtained with the *adapter sending data from an existing dataset*;
    - Data sent *respecting the time delta from different readings*;
- Embedded AI inside of the Conveyor DT;
- When vibrational data points drift, the Embedded AI returns a **not healthy state** of the associated physical asset;
- A department shut-down process is then triggered by the Department DT.



AI & DT interaction – Experimenting Embedded AI





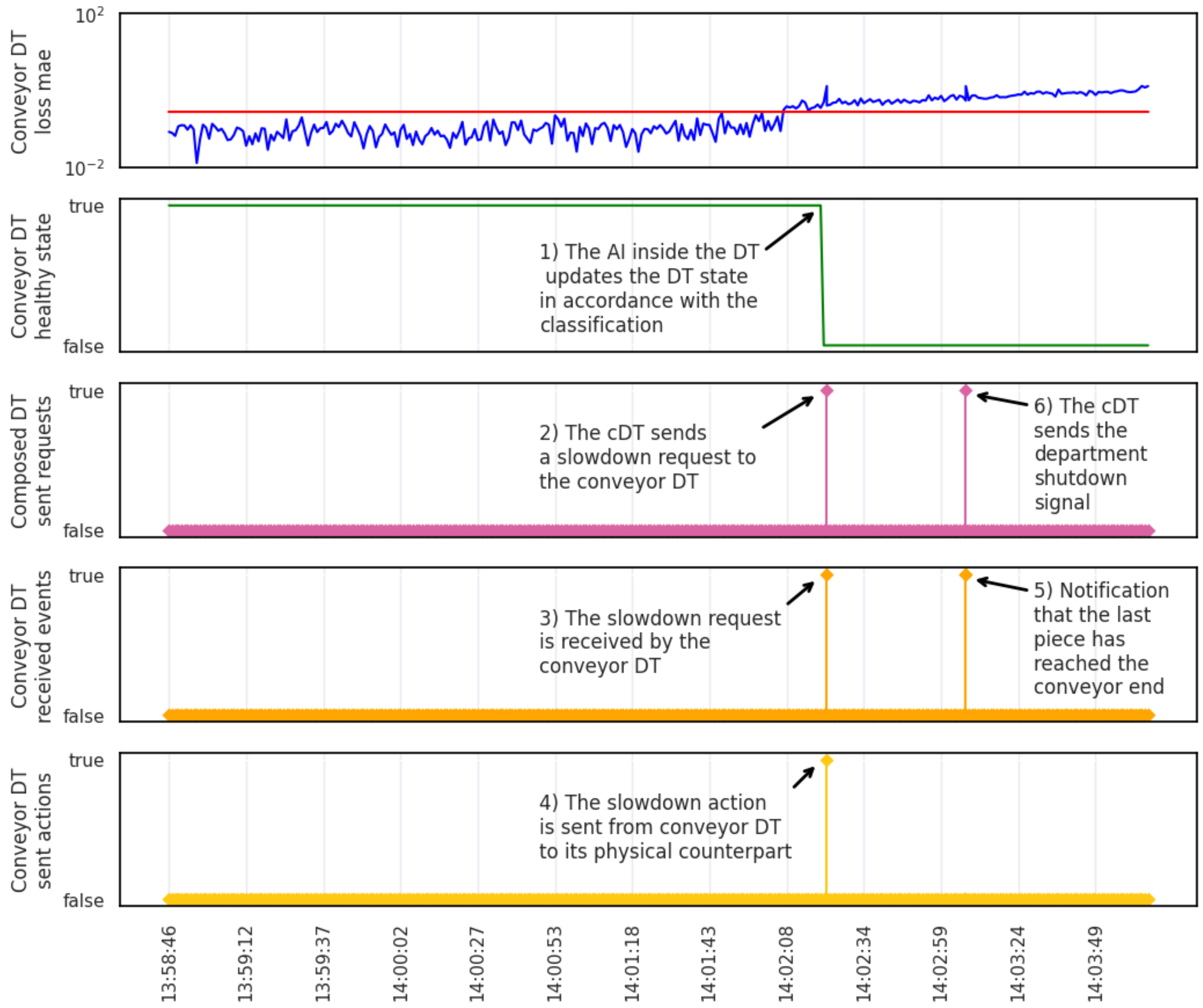


- Nasa Bearings dataset[1];
- 4 sensors for 4 bearings;
- LSTM autoencoder algorithm;
- AI model embedded in the conveyor DT.

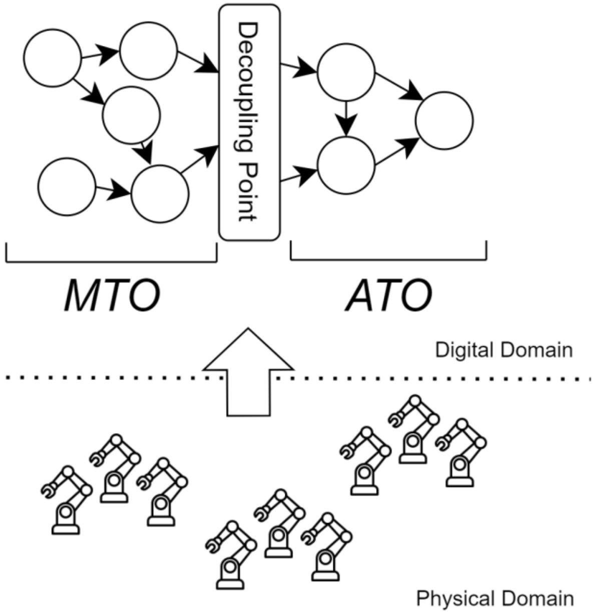
[1] Data set available at: https://www.kaggle.com/datasets/vinayak123tyagi/bearing-dataset

AI & DT interaction – Experimenting Embedded AI

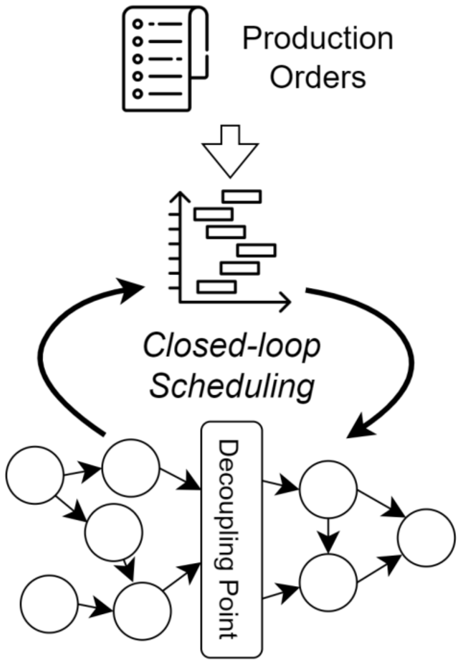
- Shut-down process:
  1. Once the conveyor is unhealthy, the information is propagated to the composed DT;
  2. The composed DT sends a slow-down request to the conveyor DT;
  3. The conveyor DT shares the request to its physical counterpart;
  4. The physical counterpart slows down;
  5. The conveyor DT waits for the last piece in the system to end its processing activities;
  6. Once the Composed DT is notified that the last piece has been processed, shuts-down the whole department.



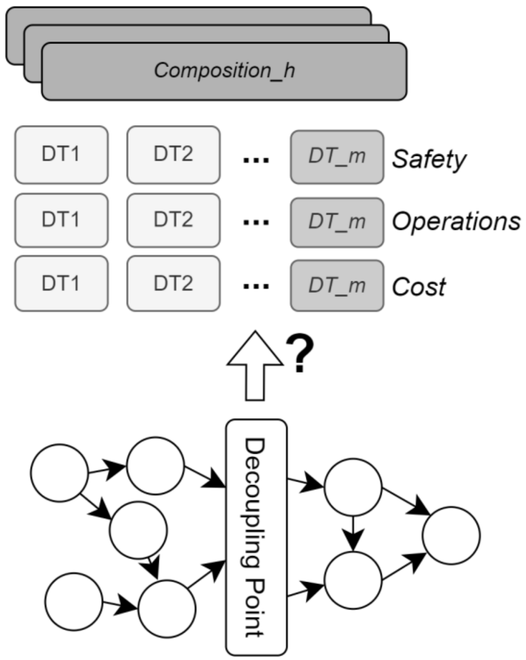
Future works



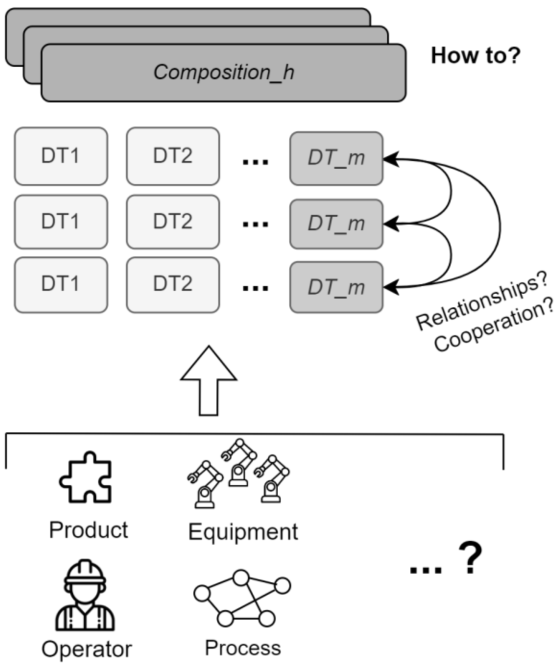
Industrial architectures



Production Scheduling



DTs Design Methods



DTs Industrial Specializations

Special thanks to …

DIPI Lab
DIstributed & Pervasive Intelligence Laboratory

Universität Stuttgart

IPVS

ISW

Thank you for your attention!

Research results: Publications

Accepted:

1. Marco Lippi, Matteo Martinelli, Marco Picone, Franco Zambonelli, *Enabling causality learning in smart factories with hierarchical digital twins*, Computers in Industry, 2023
2. Matteo Martinelli, Marco Lippi, Rita Gamberini, *Poka-yoke meets deep learning: a proof of concept for an assembly line application*, Applied Sciences, volume 12, number 21, MDPI, 2022
3. Marco Lippi, Stefano Mariani, Matteo Martinelli, Franco Zambonelli, *Individual and collective self-development: Concepts and challenges*, 17th Conference on Computer Science and Intelligence Systems (FedCSIS), 2022
4. Marco Lippi, Stefano Mariani, Matteo Martinelli, Franco Zambonelli, Self-Development and Causality in Intelligent Environments, 18th International Conference on Intelligent Environments (IE2022), 2022
5. Marco Lippi, Stefano Mariani, Matteo Martinelli, Franco Zambonelli, Franco, *Individual and Collective Autonomous Development*, arXiv preprint (arXiv:2109.11223), 2021

WIP:

1. Antonello Barbone, Samuele Burattini, Matteo Martinelli, Marco Picone, Alessandro Ricci, Antonio Virdis, *Digital Twin Continuum: a Key Enabler for Pervasive Cyber-Physical Environments*
2. Matteo Martinelli, Ann-Kathrin Splettstößer, Marco Picone, Marco Lippi, Andreas Wortmann, *Hierarchical Digital Twin Ecosystem for Industrial Manufacturing Scenarios*
3. Matteo Martinelli, Marco Lippi, Marco Picone, Andreas Wortmann, *Interaction Patterns Between AI and Digital Twin Enabled Shop-Floors in the Industrial Domain*
4. Matteo Martinelli, Marco Picone, Miguel Sellitto, *Research and application framework for Industry 4.0: a vision based on Industrial Competitive Priorities*

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- [12] Wang W. et al., *A proactive material handling method for CPS enabled shop-floor*, Robotics and Computer-Integrated Manufacturing (2020)
- [13] Friedrich J. et al., *A framework for data-driven digital twins for smart manufacturing*, Computers in Industry (2022)
- [14] Crespi N. et al., *Digital Twins: Properties, Software Frameworks, and Application Scenarios*, IT Professional (2021)
- [15] Hazra A. et al., *A Comprehensive Survey on Interoperability for IIoT: Taxonomy, Standards, and Future Directions*, ACM Comput. Surv. (2021)
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