Artificial Intelligence for Business Intelligence

Week 7: AI4BI in Smart Manufacturing

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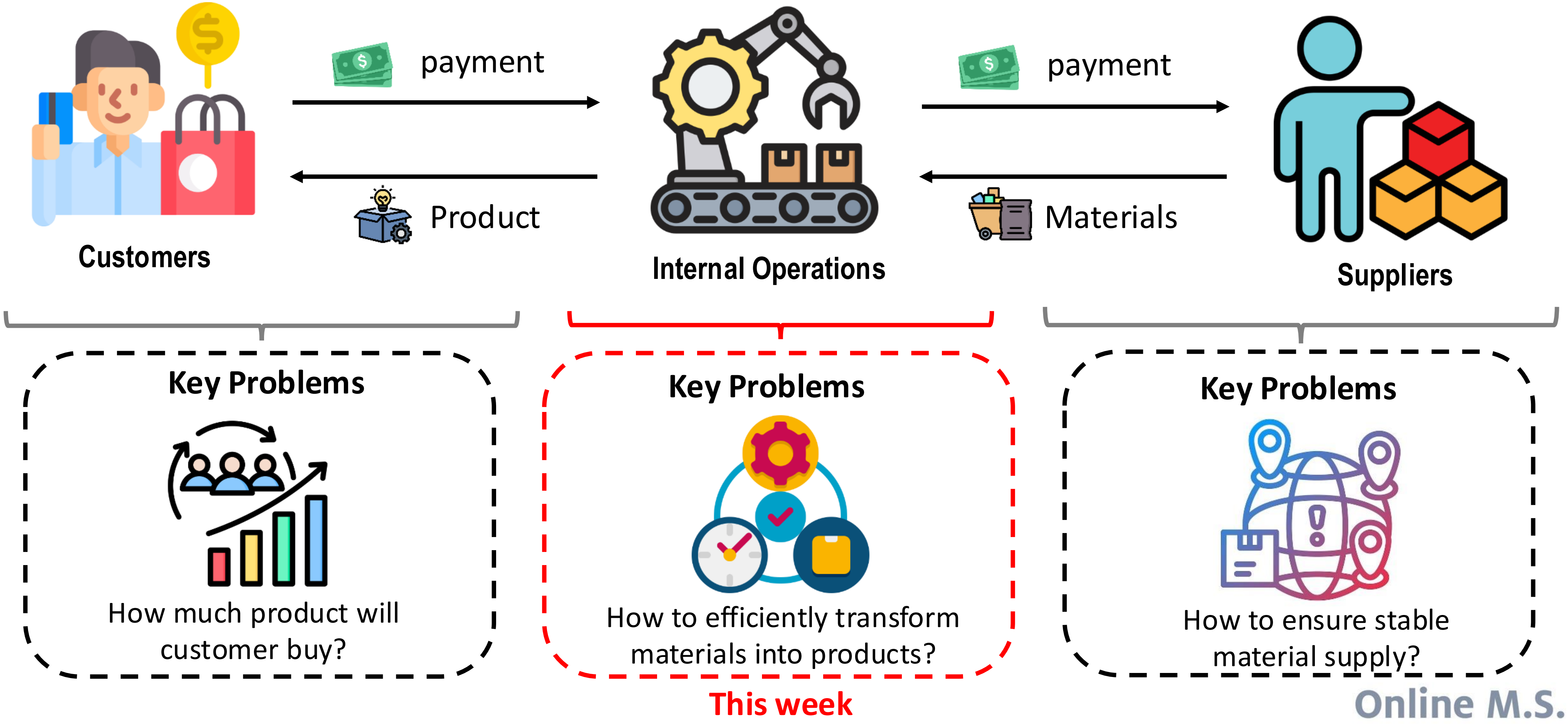
Today's Learning Objectives

- Understand the development and key components in industry 3.0 and 4.0.
- Describe the current approaches and challenges in managing machine failure and enhancing production efficiencies.
- Understand the key type of data from a smart factory that enables AI analytics.
- Explain the common AI methods for smart manufacturing and their corresponding data characteristics.
- Understand how smart manufacturing deliver business value through a dashboard.

Business Operation



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The Manufacturing Industry

- In the context of physical goods, manufacturing is the fundamental engine for value creation for a company.

- The manufacturing industry transforms raw materials (from suppliers) into finished products (to meet customers' demand).

- To mass-produce standardized products, companies often use a production line.

The Manufacturing Industry

- The production line often involves multiple steps.
  - For example, to assemble a car, it has to go through chassis & frame, body welding, painting, engine & drivetrain, and final assembly.

The Manufacturing Industry

- The rapid development of information technology has enabled **industrial robots (IR)** to undertake manual tasks in the production line.
  - This shields human workers from a hazardous working environment (e.g., painting and welding create toxic fumes and extreme heat).

- **Programmable Logic Controllers (PLC)** execute specific industrial logic and functions to control *IRs* through *axes*.
  - They enhance the operational precision and consistency through a fixed program.

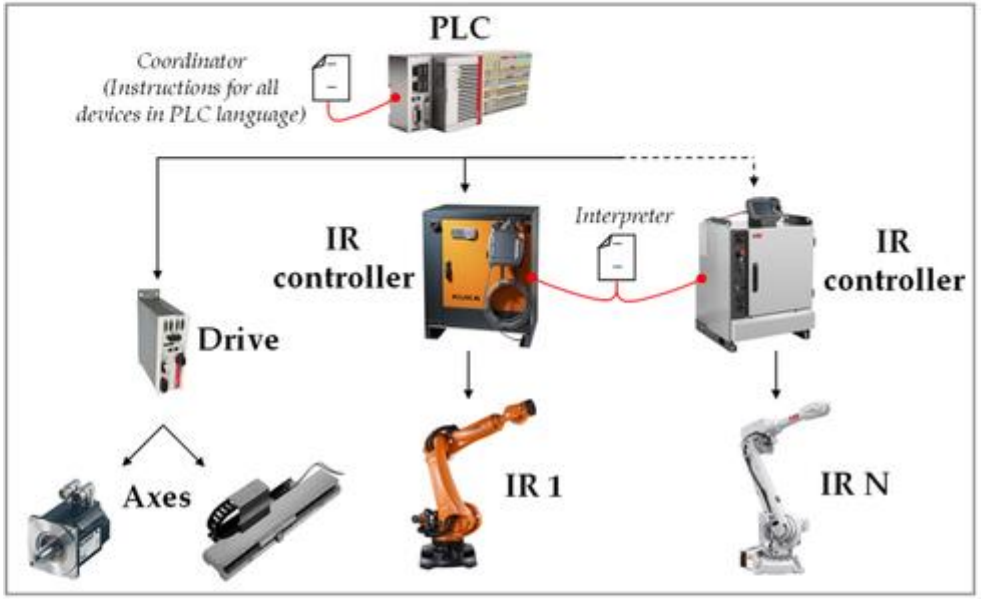


Image from: Bilancia, P., Schmidt, J., Raffaeli, R., Peruzzini, M., & Pellicciari, M. (2023). An overview of industrial robots control and programming approaches. *Applied Sciences*, *13*(4), 2582.

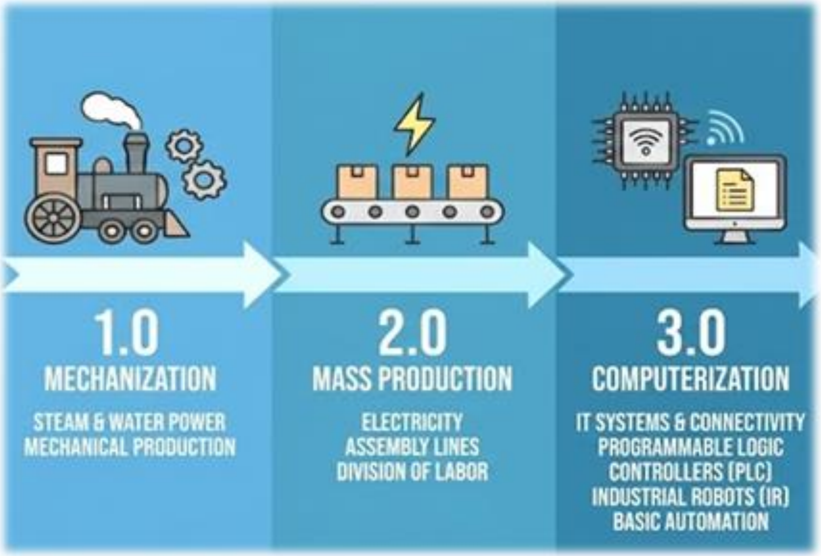
The Manufacturing Industry

- Most production lines are now automated by PLC-controlled specialized machinery.
  - The use of pre-defined logic and parameters within PLC also ensures high precision for repetitive tasks.

- By configuring the PLC parameters, a production line can also produce multiple types of products
  - For example, an automotive production line can produce sedans, SUVs, and trucks.

The Manufacturing Industry

- PLC-controlled production line works well for traditional mass production (e.g., soft drink bottling) as they are:
  - **High-volume:** A single line can process tens of thousands of bottles per hour
  - **Low-variety:** Every single unit is identical in shape, weight, and volume
  - **High error tolerance**: a defective unit can be discarded or reworked with minimal impact on overall profitability.

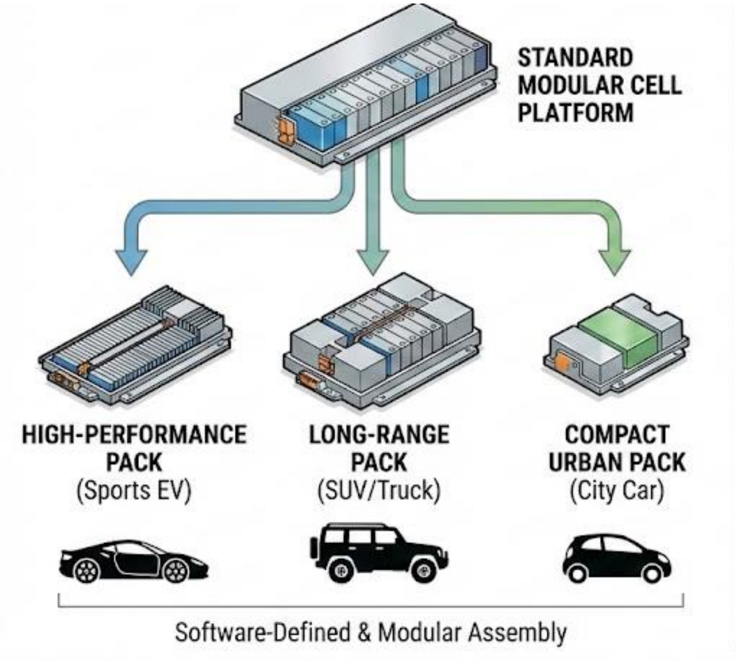


- This automated production line operated through pre-defined logic is often referred to as **Industry 3.0**.

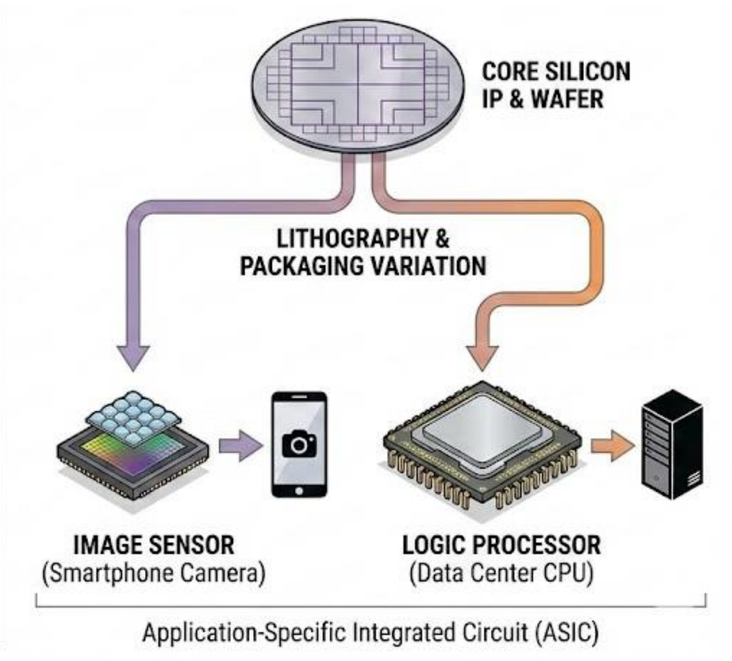
Modern Manufacturing

- Recently, there’s a growing need for advanced products with **high value and complexities** (e.g., EV battery, chips, aerospace components).
  - They often require functional integration into sophisticated systems.
- To this end, modern manufacturing is evolving into **smart factories** that can handle **high precision** and **mass customization.**

EV Batteries



Semiconductor Chips



Modern Manufacturing

- To ensure high production **precision**, a smart factory is often equipped with **Industrial Internet of Things (IIoT)**.

- IIoT integrates thousands of sensors into equipment in a factory to gather detailed data (e.g, vibration, heat, pressure, chemical flows, sound)

- This provides complete transparency into the production line, helping gather fine-grained information.

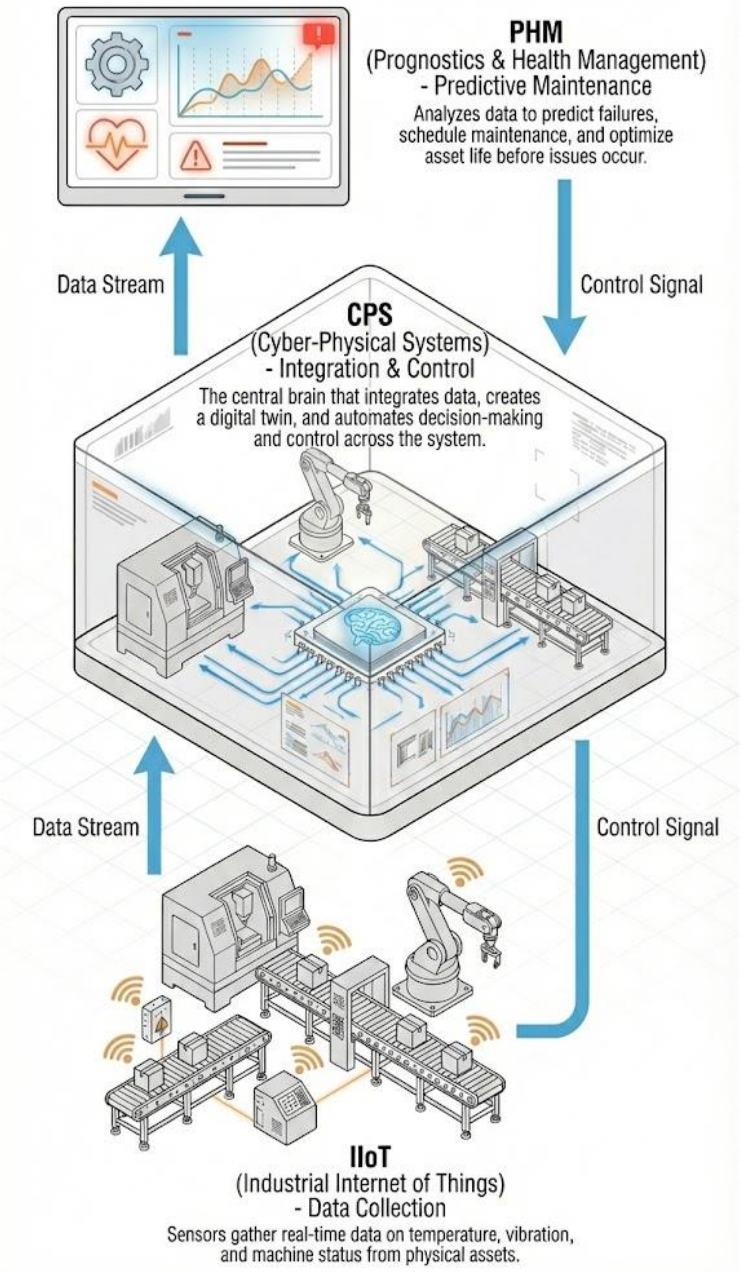
From https://www.advantech.com/en-us/resources/faq/what-is-industrial-internet-of-things-iiot-how-does-iiot-work

Modern Manufacturing

- The data gathered from IIoT is managed by the **Cyber-Physical Systems (CPS).**

- CPS acts as the central brain integrating physical machines with digital models for real-time control (e.g., robot movement path control)

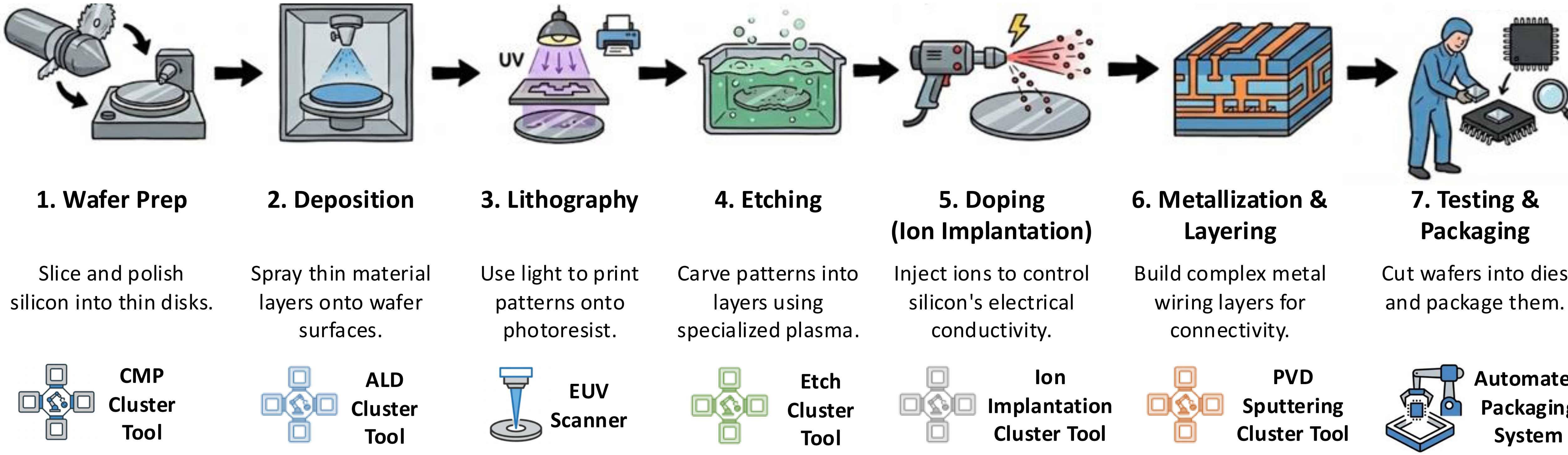
- Within CPS, the **Prognostics and Health Management (PHM)** provides a software interface to monitor and manage the production process.



Reference: Sahoo, S., & Lo, C. Y. (2022). Smart manufacturing powered by recent technological advancements: A review. *Journal of Manufacturing Systems*, *64*, 236-250.

Modern Manufacturing

- To allow **mass customization**, a smart factory is often equipped with advanced machineries.
  - For example, semiconductor manufacturing requires distinct type of equipment across 7 major production steps.



Modern Manufacturing – Semiconductor

- **A cluster tool** is a type of equipment that is widely used in semiconductor manufacturing.
  - It is equipped with multiple processing modules (chambers) that perform distinct functions
  - Multiple types of chips (e.g., chips for image sensor, logic processor) can be processed in a single cluster tool.

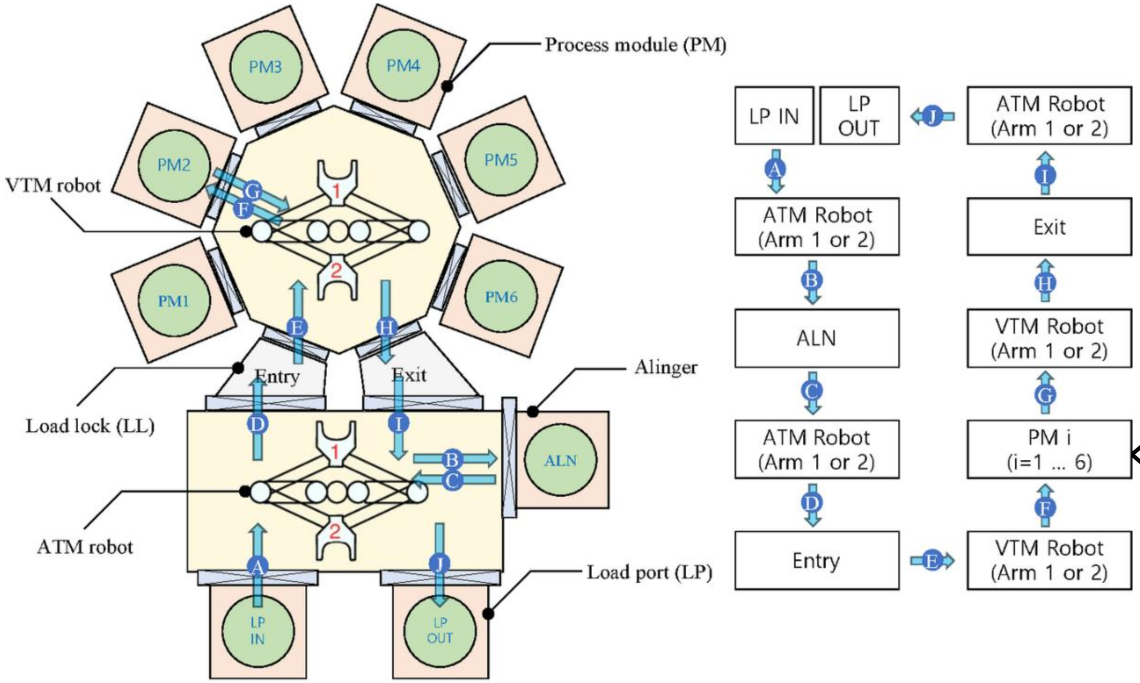
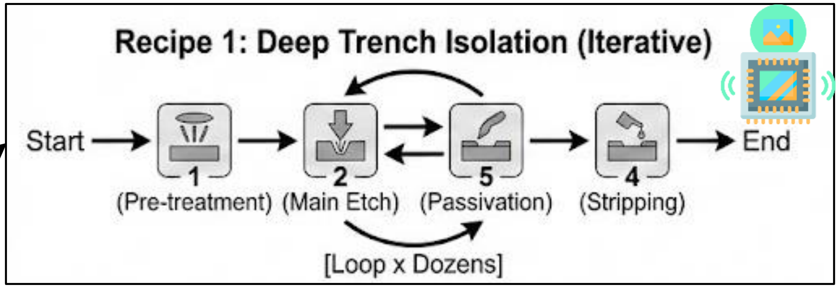
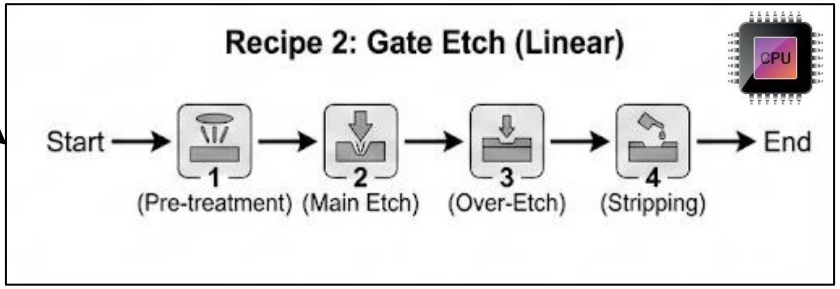


Image from Choi, J., & Kim, S. B. (2025). Deep reinforcement learning for scheduling semiconductor cluster tools in varying configurations. *Scientific Reports*.

Image Sensor in Smartphone camera



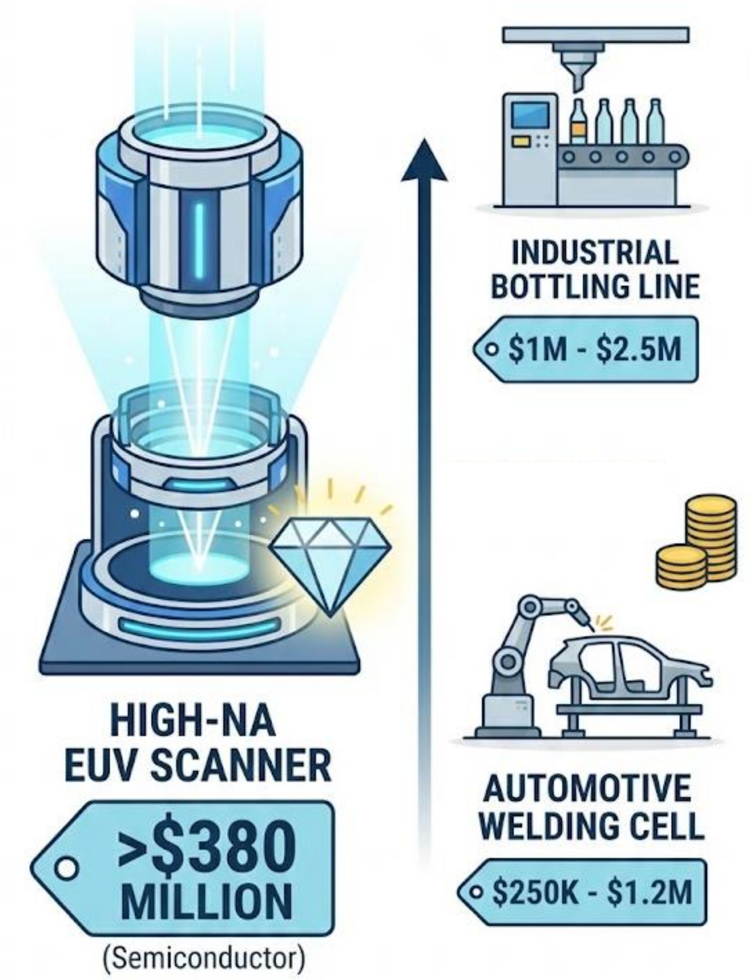
Logic processor in CPU



Modern Manufacturing

- These advanced machineries are often of high cost due to their high precision and specialization.
  - E.g., a cluster tool can cost more than $150 million, a high-NA EUV Scanner can cost more than $380 millions
- Moreover, the finished product often has a high selling price
  - E.g., a 12-inch silicon wafer has an average selling price of **US$ 20,000**.
- Therefore, it is crucial to enhance the production yield.

$$\text{Yield} = \frac{\text{Actual Output of Good Product}}{\text{Theoretical Maximum Output}}$$



References:
- https://www.forbes.com/sites/greatspeculations/2026/01/09/what-2026-has-in-store-for-asml-high-na-euv-dram/
- https://www.techpowerup.com/339570/tsmc-will-have-four-2-nm-plants-by-2026-producing-60-000-wafers-per-month#:~:text=Although%20each%20300%20mm%20wafer,nm%20and%205%20nm%20nodes.

Modern Manufacturing

- Companies usually maximize the production yield from two aspects:
  1. Enhance the overall production **efficiency** by:
     - **Minimizing Makespan (**the time difference between the completion time of the last job and the start time of the first job)
     - **Maximizing Throughput** (amount of product produced per a specific period of time)
  2. **Prevent machine failure** in advance to avoid interruptions and wasting production resources

- Achieving them requires analyzing a large volume of data collected from IIoT and CPS.

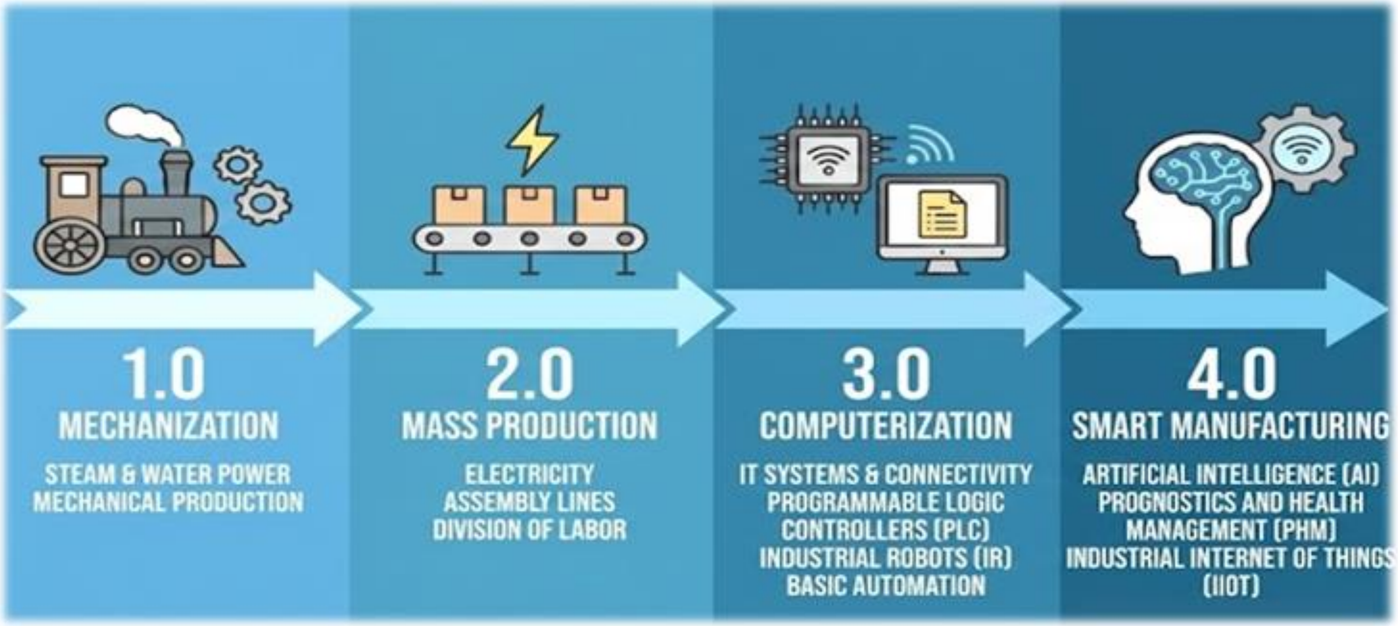
- Therefore, Artificial Intelligence (AI) has been largely incorporated into PHM to facilitate the analysis.

Reference: Sahoo, S., & Lo, C. Y. (2022). Smart manufacturing powered by recent technological advancements: A review. *Journal of Manufacturing Systems*, *64*, 236-250.

Smart Manufacturing: Industry 4.0

- **Smart Manufacturing** is a paradigm shift that integrates technologies (IIoT, CPS, PHM) and AI to optimize production processes, entering the **Industry 4.0** era.

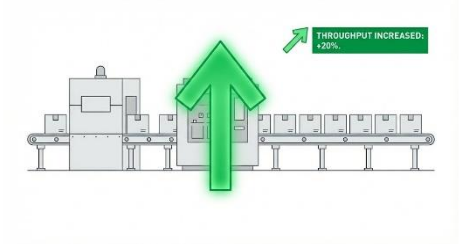
- The AI4BI development process can be applied to guide the AI development in Smart Manufacturing.



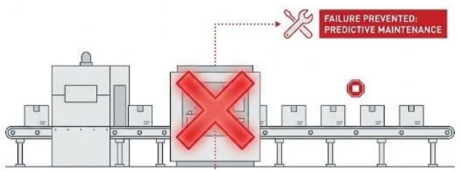
Reference: Sahoo, S., & Lo, C. Y. (2022). Smart manufacturing powered by recent technological advancements: A review. *Journal of Manufacturing Systems*, *64*, 236-250.

AI4BI Development Process for Smart Manufacturing

Smart Manufacturing Problem Identification



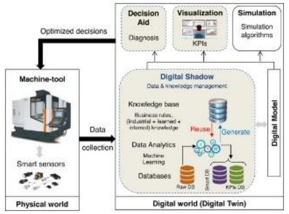
Efficiency Enhancement



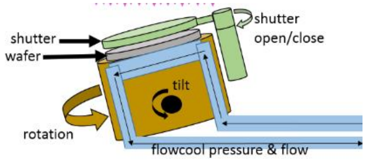
Failure Management

Smart Factory Data Collection

Historical Production Log

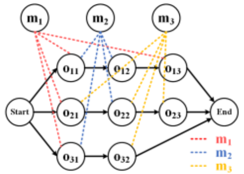


Simulator and Digital Twin

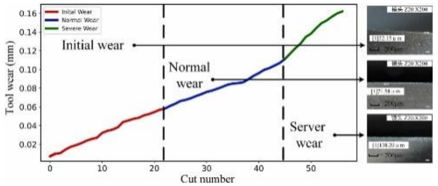


IIoT Data

AI-enabled Analytics



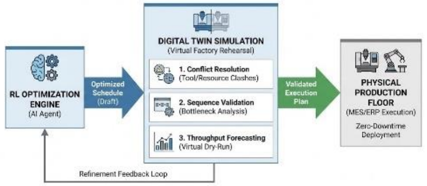
Production Optimization



Downtime Prediction

Defect Detection

Value Delivery

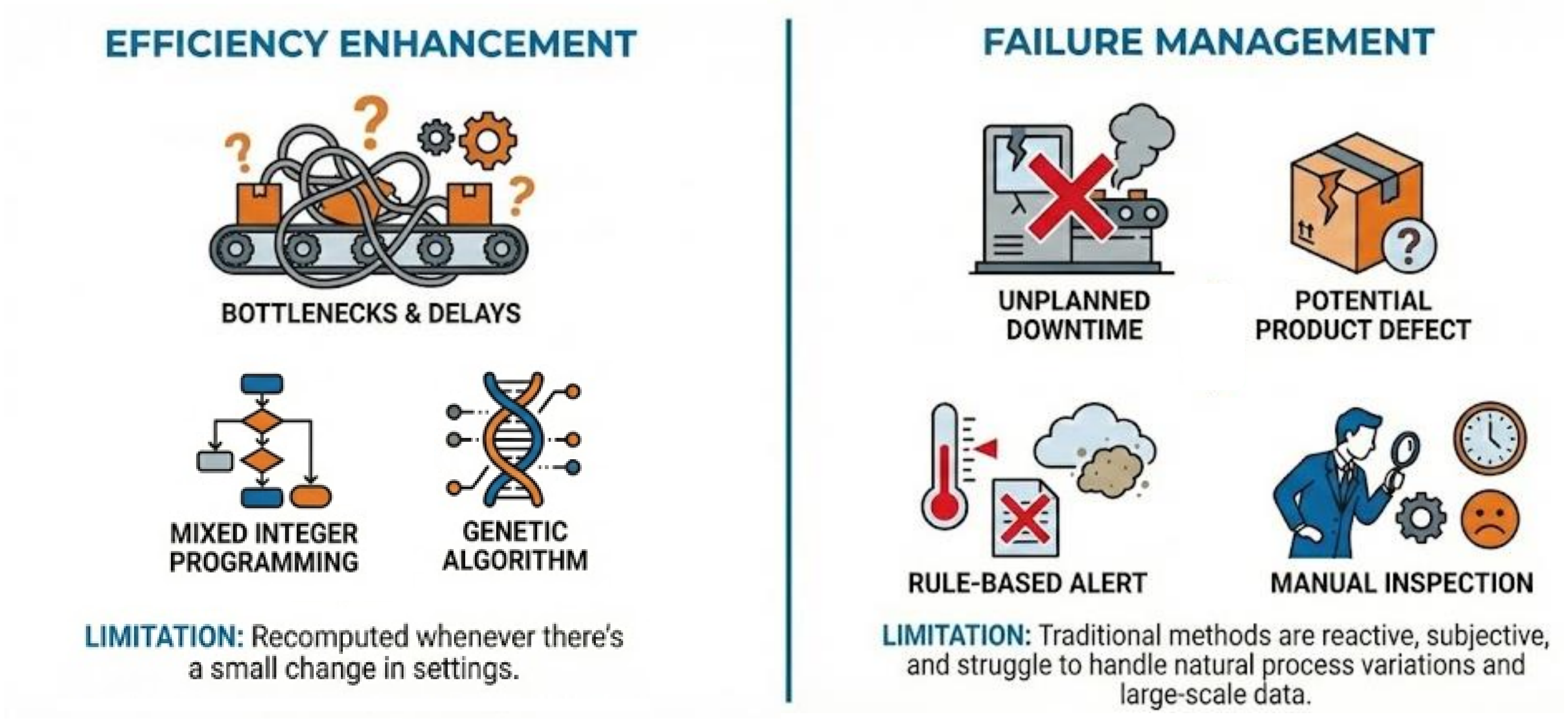


Digital Twin for Efficiency Enhancement

PHM Dashboard for Failure Management

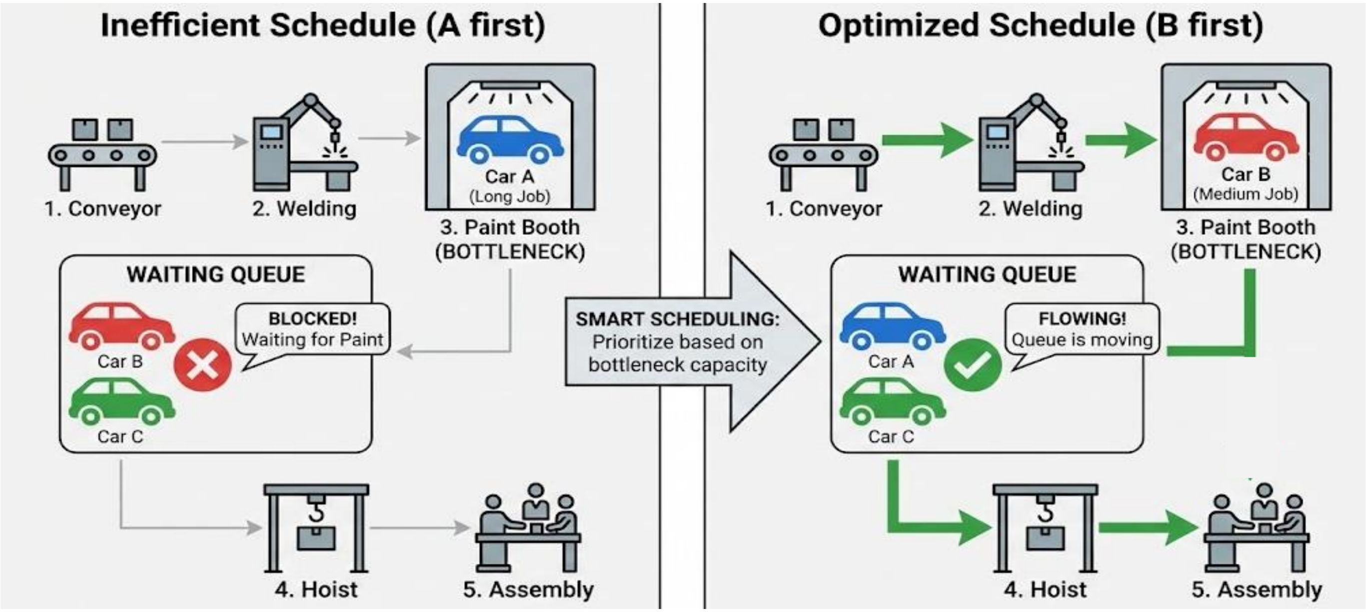
Step 1: Smart Manufacturing Problem Identification

- To enhance the production yield in the modern manufacturing industry, factory managers often focus on **efficiency enhancement** and **failure management**.



Efficiency Enhancement

- A 1% enhancement in manufacturing throughput can create up to $150 million in annual value for a single modern advanced production line.
- Therefore, companies often want to determine a good schedule that can minimize the makespan or maximize the throughput.



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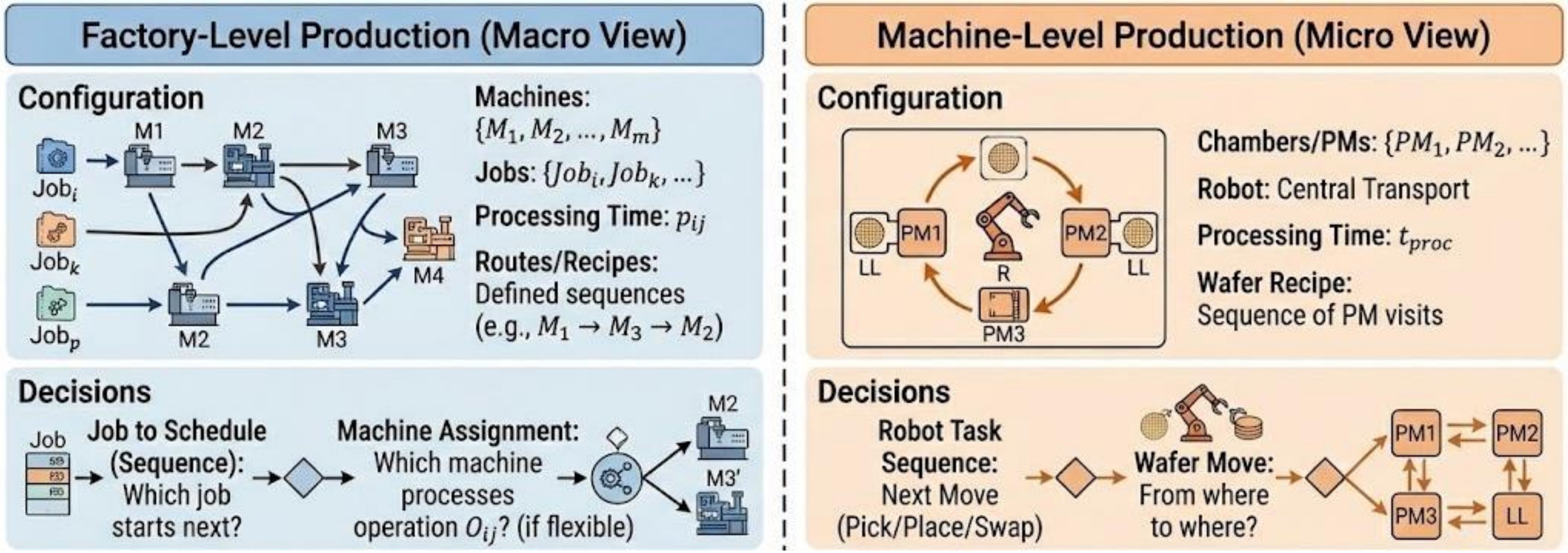
Efficiency Enhancement

- The optimization can be done at :
  - **Factory-level** to coordinate multiple machines
  - **Machine-level** to coordinate the product flow between multiple modules in a single machine



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Efficiency Enhancement

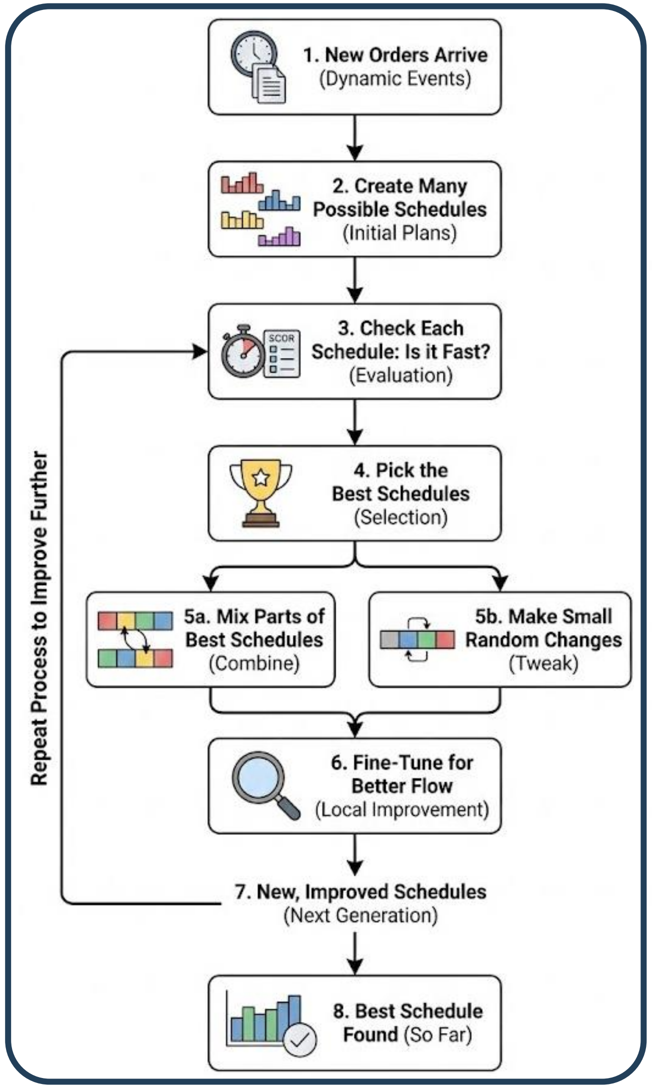
- **Traditional methods**:
  - **Mixed integer programming (MIP)**: find the mathematically optimal schedule by solving equations within defined constraints
  - **Genetic algorithm (GA)**: evolve optimal schedules by repeatedly selecting and combining the most efficient production plans

MIP in Production Optimization

Objective: Minimize makespan	$\min \; C_{max}$	
Non-negative start time	s.t. $x_{ij} \geq 0,$	$\forall j \in J, i \in M$
Jobs follow operation sequence	$x_{\sigma_h^j, j} \geq x_{\sigma_{h-1}^j, j} + p_{\sigma_{h-1}^j, j},$	$\forall j \in J, h = 2, \ldots, m$
Prevents overlapping jobs on machines	$x_{ij} \geq x_{ik} + p_{ik} - V \cdot z_{ijk},$	$\forall j, k \in J, j < k, i \in M$
Enforces machine processing order logic	$x_{ik} \geq x_{ij} + p_{ij} - V \cdot (1 - z_{ijk}),$	$\forall j, k \in J, j < k, i \in M$
Defines makespan as completion time	$C_{max} \geq x_{\sigma_m^j, j} + p_{\sigma_m^j, j},$	$\forall j \in J$
Ordering variables must be binary	$z_{ijk} \in \{0, 1\},$	$\forall j, k \in J, i \in M$

constraints

GA in Production Optimization



Reference:

- Ku, W. Y., & Beck, J. C. (2016). Mixed integer programming models for job shop scheduling: A computational analysis. *Computers & Operations Research*, 73, 165-173.
- Kundakcı, N., & Kulak, O. (2016). Hybrid genetic algorithms for minimizing makespan in dynamic job shop scheduling problem. *Computers & Industrial Engineering*, *96*, 31-51.

Efficiency Enhancement

- While MIP guarantees a global optimal solution, it is computationally expensive because it must explore an exponentially large search space.
  - For a factory with just 5 machines with multiple jobs having 10 different operation sequence, reaching an optimum requires over 3 days of computational time.
- GA addresses this by evolving "good enough" solutions through selection and mutation, providing results in minutes rather than days.
- However, MIP and GA require parameters to be deterministic numbers.
  - Real production environments are often **stochastic** (processing time in a machine is not fixed).
- Moreover, MIP and GA have to be recomputed even with a small change, such as:
  - Adjustment in machine specification (speed, capacity)
  - Processing delays (from unexpected time variation)
  - Production disruption (e.g., machine breakdown)

Efficiency Enhancement – Summary

Stakeholder

- **Primary user**: Production managers
- **Responsibility**: Enhance production yield through proper resource planning and equipment management

Scenario

- **Task**: Production optimization
- **Process**: Identify a good schedule for the production line

Current approach

- **Data source**: Machine specification, mathematical formulation
- **Current method**: Genetic algorithm, MIP

Limitation of this approach

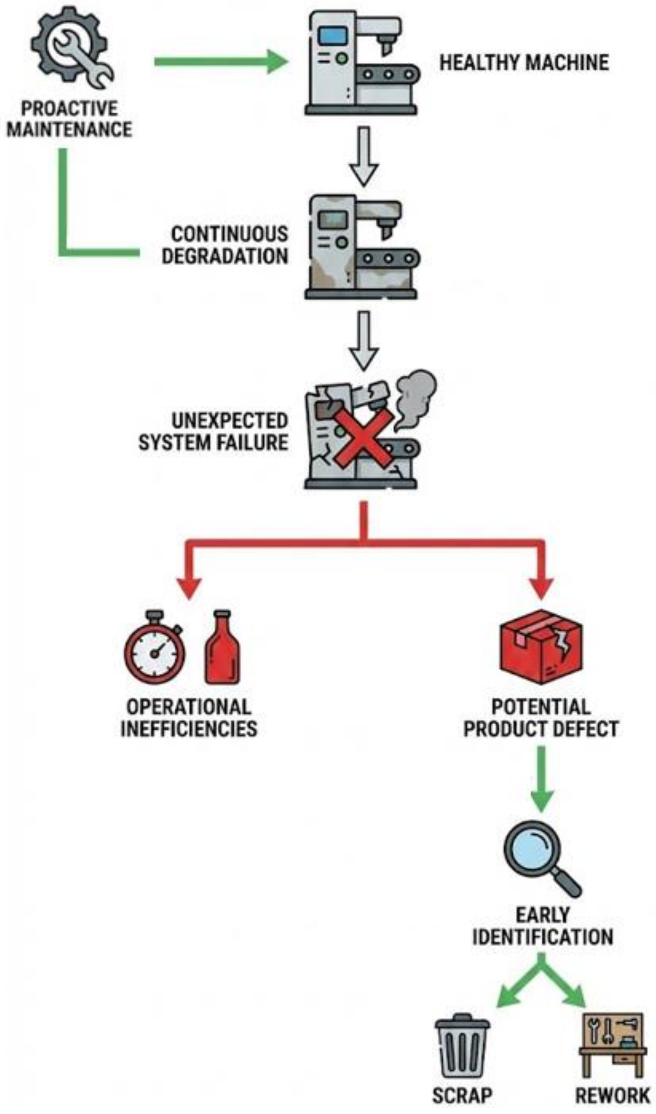
- **Data-wise**: Require fixed numbers as the input parameter
- **Process-wise**: The schedule has to be recomputed if any changes happen

Failure Management

- Industrial machinery is subject to continuous physical degradation.
  - Minor deviations in operational parameters eventually culminate in unexpected system failure.

- Unexpected machine failure can lead to significant operational inefficiencies and potential product defects.

- Therefore, companies perform proactive maintenance to ensure production stability.
  - If a product defect happens, identifying it helps scrap or rework a part at the beginning of the line



Failure Management

- **Traditional methods**
  - **Preventive maintenance**: Maintenance is performed at fixed intervals (e.g., every 500 hours)
  - **Rule-based alert**: generate an alert when a certain parameter (e.g., temperature) or product geometry is wrong.
  - **Manual inspection**: directly observe machine condition and products

- **Limitations**
  - Preventive maintenance can lead to over-maintenance
  - Rule-based alert cannot handle natural variance well (e.g., a normal variation in temperature or a dust on the product)
  - Manual inspection is highly subjective and time-consuming
    - By the time a human technician analyzes the data and spots a trend, the machine has often already reached a critical failure point and create defect productions.

Reference: Mohan, T. R., Roselyn, J. P., Uthra, R. A., Devaraj, D., & Umachandran, K. (2021). Intelligent machine learning based total productive maintenance approach for achieving zero downtime in industrial machinery. *Computers & Industrial Engineering*, *157*, 107267.

Operational Efficiency – Summary

Stakeholder

- **Primary user**: Production managers
- **Responsibility**: Enhance production yield through proper resource planning and equipment management

Scenario

- **Task**: Ensure the production process is working normally
- **Process**: Determine whether a machine will fail and whether each product (or work-in-progress) is defect

Current approach

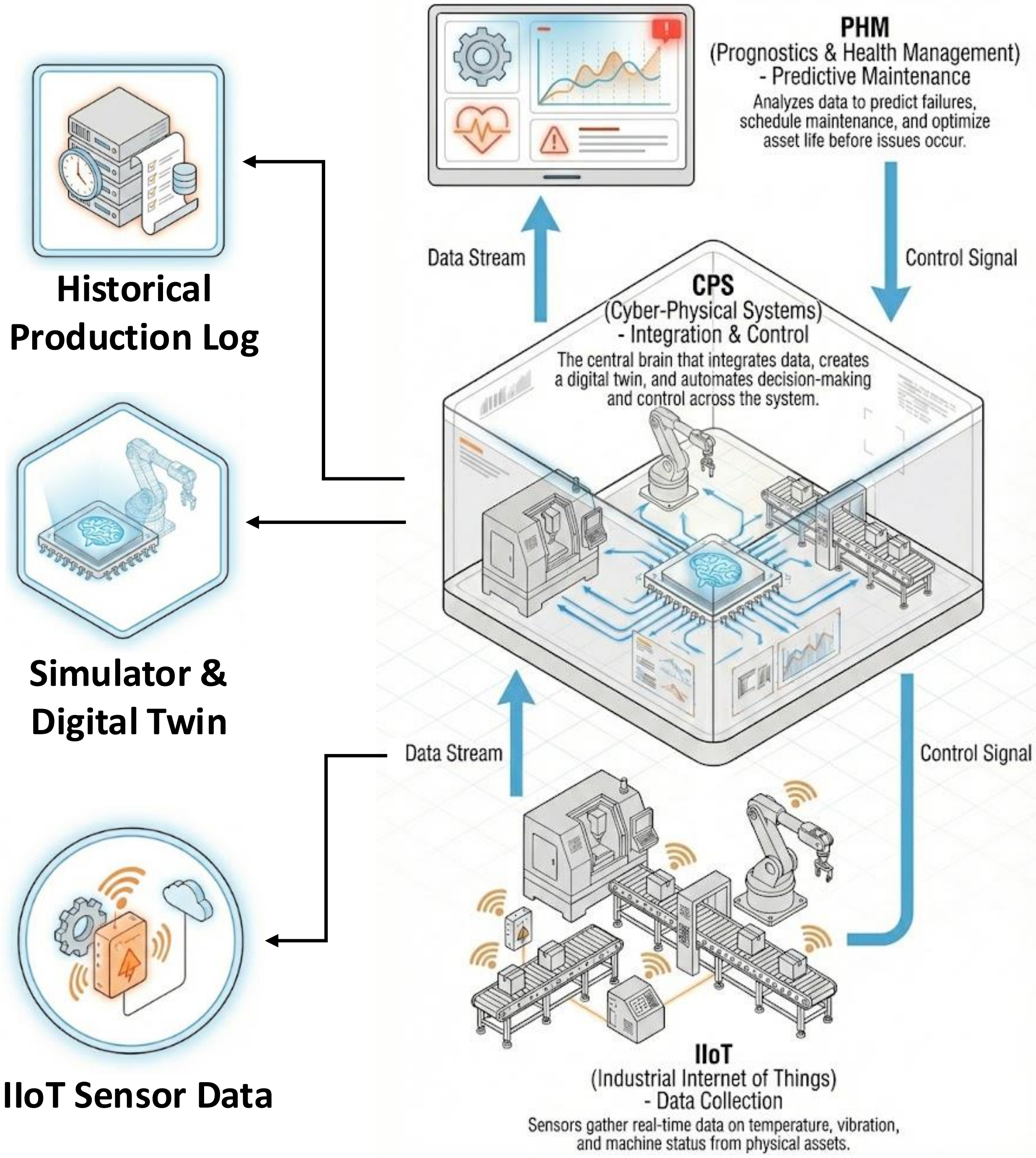
- **Data source**: machine status, product image
- **Current method**: preventive maintenance, rule-based alert, manual inspection

Limitation of this approach

- **Data-wise**: Rule-based alert cannot handle natural variance well
- **Process-wise**: Manual inspection is time-consuming and highly subjective

Step 2: Smart Factory Data Collection

- Three types of data are essential to enable smart manufacturing.
- **Historical production log**: from the Manufacturing Execution System (often accessible from CPS)
- **Simulator & Digital Twin**: built inside CPS
- **IIoT Sensor Data**: directly from IIoT sensors (organized in CPS)



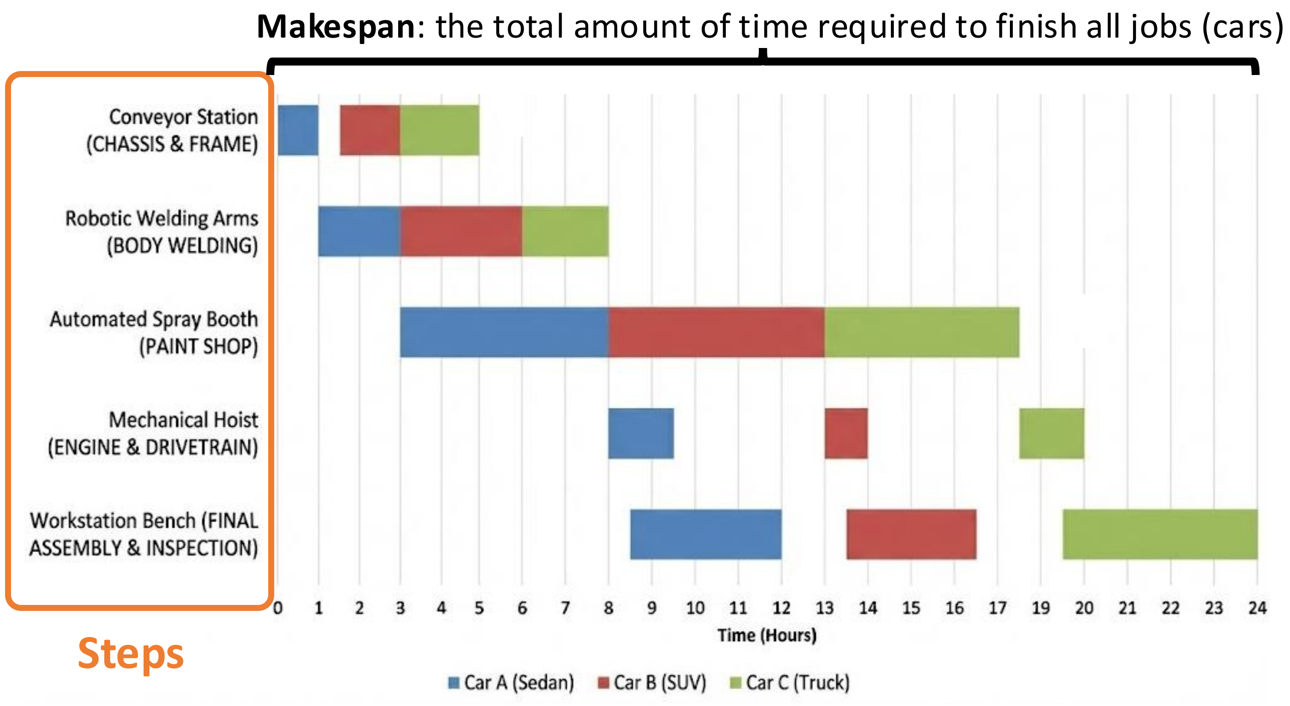
Historical Production Log

- Historical production logs record the activity of the machines, including timestamp, Job ID, Machine (workstation) ID, and event type
- **Source**: CPS (specifically the Manufacturing Execution System)
- **Collection method**: direct database query, csv export

Log ID	Timestamp	Job ID	Product Type (Color)	Workstation ID	Station Name	Event Type
L-0001	2024-05-20 06:00:00	JOB-A-101	Sedan (Blue)	WS-01	Conveyor Station	Process Start
L-0002	2024-05-20 07:00:00	JOB-A-101	Sedan (Blue)	WS-01	Conveyor Station	Process Complete
L-0003	2024-05-20 07:00:05	JOB-A-101	Sedan (Blue)	WS-02	Robotic Welding Arms	Process Start
L-0004	2024-05-20 07:00:00	JOB-B-102	SUV (Red)	WS-01	Conveyor Station	Process Start
L-0005	2024-05-20 09:00:00	JOB-A-101	Sedan (Blue)	WS-02	Robotic Welding Arms	Process Complete
L-0006	2024-05-20 09:00:10	JOB-A-101	Sedan (Blue)	WS-03	Automated Spray Booth	Process Start
L-0007	2024-05-20 09:00:00	JOB-B-102	SUV (Red)	WS-01	Conveyor Station	Process Complete
L-0008	2024-05-20 09:00:05	JOB-B-102	SUV (Red)	WS-02	Robotic Welding Arms	Process Start
L-0009	2024-05-20 09:00:00	JOB-C-103	Truck (Green)	WS-01	Conveyor Station	Process Start
L-0010	2024-05-20 11:00:00	JOB-C-103	Truck (Green)	WS-01	Conveyor Station	Process Complete
L-0011	2024-05-20 12:00:00	JOB-B-102	SUV (Red)	WS-02	Robotic Welding Arms	Process Complete
L-0012	2024-05-20 12:00:05	JOB-C-103	Truck (Green)	WS-02	Robotic Welding Arms	Process Start
L-0013	2024-05-20 13:00:00	JOB-B-102	SUV (Red)	WS-04	Mechanical Hoist	Process Start
L-0014	2024-05-20 14:00:00	JOB-A-101	Sedan (Blue)	WS-03	Automated Spray Booth	Process Complete
L-0015	2024-05-20 14:00:10	JOB-A-101	Sedan (Blue)	WS-04	Mechanical Hoist	Process Start

Historical Production Log – Gantt Chart

- A historical production log can often be represented as a Gantt chart to understand the overall production process and identify any inefficiencies



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Simulator and Digital Twins

- A simulator is a virtual modeling environment designed to imitate the behavior of a real-world manufacturing process over time.

- Two types of data are required to build a simulator:
  - **Hisotrical Production Log** to understand the actual processing time distribution, frequency of changeovers
  - **Machine specifications**: machines and chambers, how they are connected

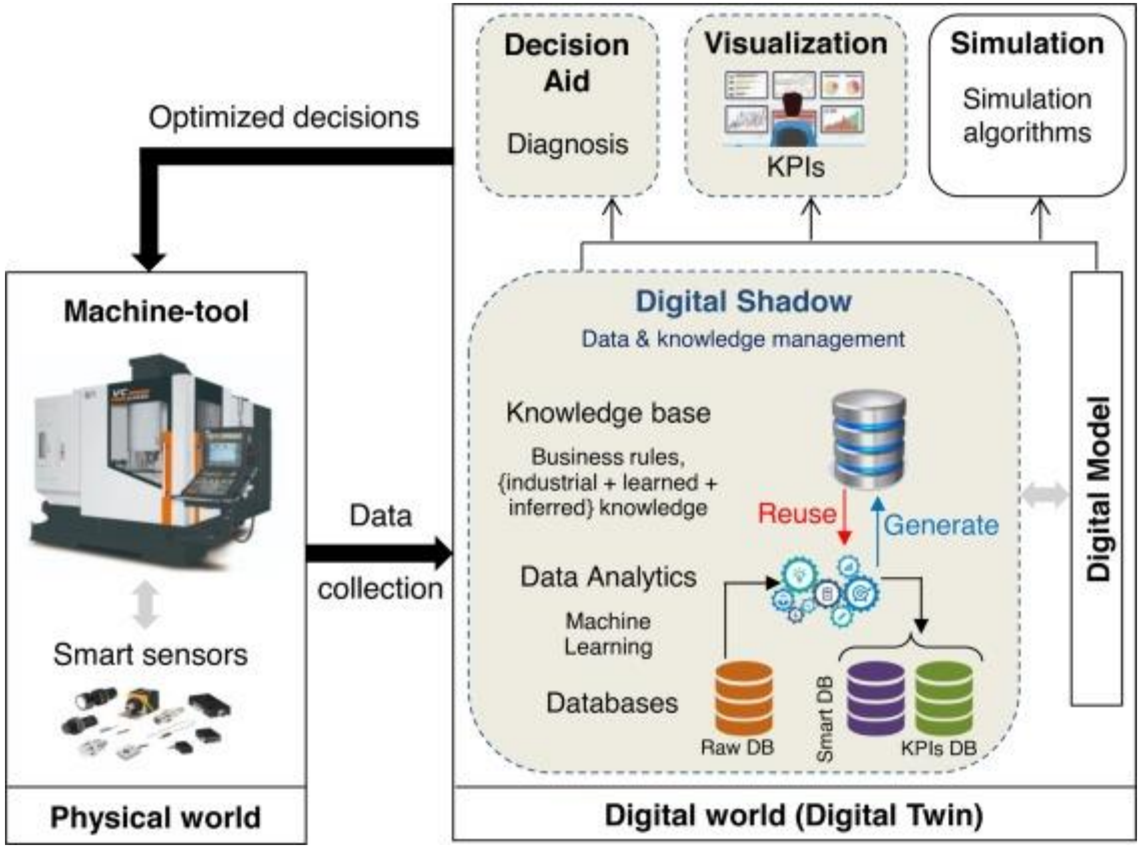
- **Common open-source options**: job shop lab (factory-level), cluster tool simulator (machine-level)
  - Companies can adapt them to their environment based on historical production log and machine specifications
  - They are usually built with **Python Gymnasium** (ready for reinforcement learning).

Reference:

- **Job Shop Lab**: https://github.com/proto-lab-ro/jobshoplab, from Hoss, J., Schelling, F., & Klarmann, N. (2025, August). A Production Scheduling Framework for Reinforcement Learning Under Real-World Constraints. In *2025 IEEE 21st International Conference on Automation Science and Engineering (CASE)* (pp. 1736-1743). IEEE.
- **Cluster Tool Simulator**: https://github.com/jongwon8707/Semiconductor_ClusterTool_Simulator from Choi, J., & Kim, S. B. (2025). Deep reinforcement learning for scheduling semiconductor cluster tools in varying configurations. *Scientific Reports*.

Simulator and Digital Twins

- Companies often integrate **IIoT live sensor data** from the real production environment to synchronize and enhance their virtual simulator
- This evolves into a **digital twin**, which is a virtual representation of the machine in the physical world.
- **Benefit**:
  - Simulate when the machine will break down
  - Allow the AI agent to learn and optimize the production schedule
- **Common Framework** (middleware): Eclipse Ditto, BaSyx, Nvidia Isaac Sim
  - Allow a company turn a standalone simulator or piece of equipment into a true Digital Twin.



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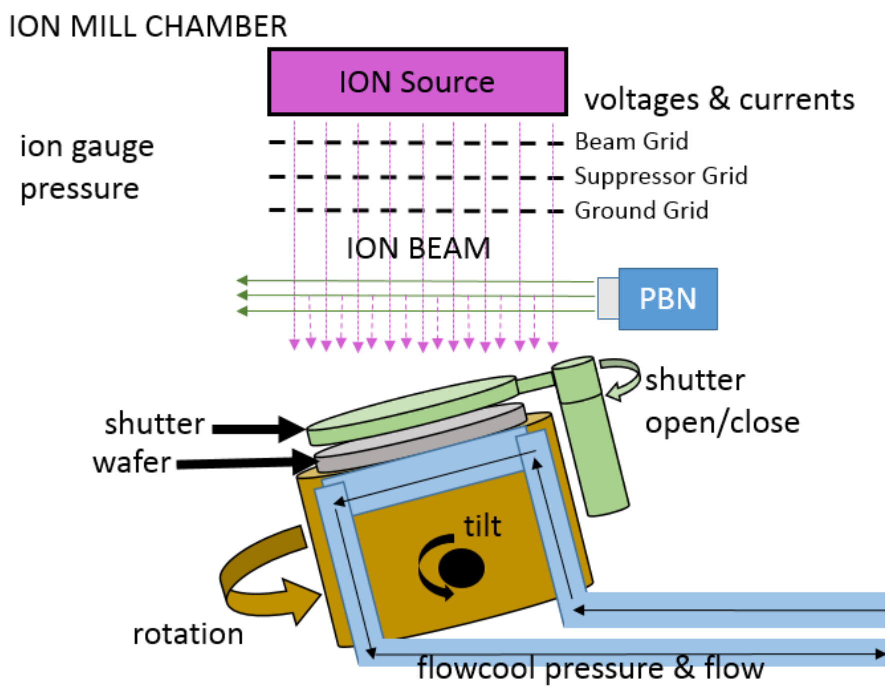
Reference: Tao, F., Xiao, B., Qi, Q., Cheng, J., & Ji, P. (2022). Digital twin modeling. *Journal of Manufacturing Systems*, *64*, 372-389.

IIoT Sensor Data

- IIoT data are the data collected from IIoT attached to the machines, such as:
  - **Physical signs** (e.g., vibration, temperature)
  - **Electrical signals** (e.g., voltage, current)
  - **Process variables** (e.g., flow rates, gas pressures)
- **Source**: IIoT (organized in CPS)
- **Collection method**: direct database query, csv export, real-time streaming (e.g., for digital twin)
- **Open source example**: PHM Data Challenge Etching tool fault detection dataset from the PHM Society.

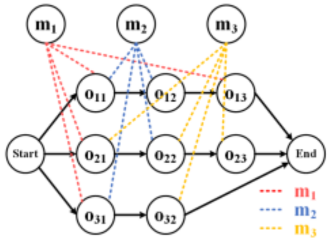


References:
- **Etching tool fault detection dataset**: https://github.com/makinarocks/awesome-industrial-machine-datasets/tree/master/data-explanation/PHM%20Data%20Challenge%2018
- **Image** from: https://phmsociety.org/conference/annual-conference-of-the-phm-society/annual-conference-of-the-prognostics-and-health-management-society-2018-b/phm-data-challenge-6/

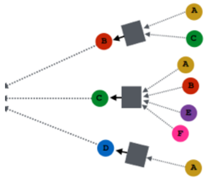
Step 3: AI-enabled Analytics

- AI-enabled analytics are designed to facilitate efficiency enhancement and failure management at different stages of operation.

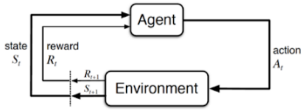
1. Production Optimization



How to schedule the production?



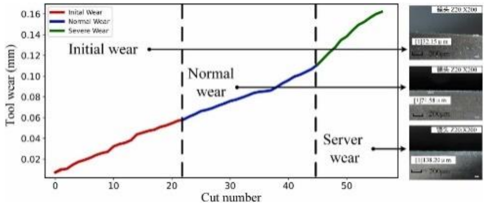
GNN



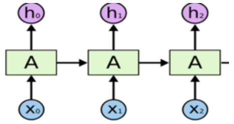
RL

Before Production

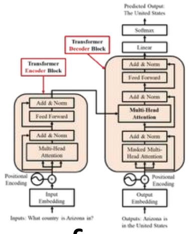
2. Downtime Prediction



How is our machines



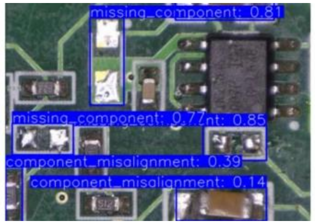
RNN, LSTM, GRU



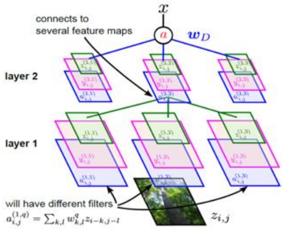
Transformer-based Models

During Production

3. Defect Detection



How is our product?



CNN

After Production

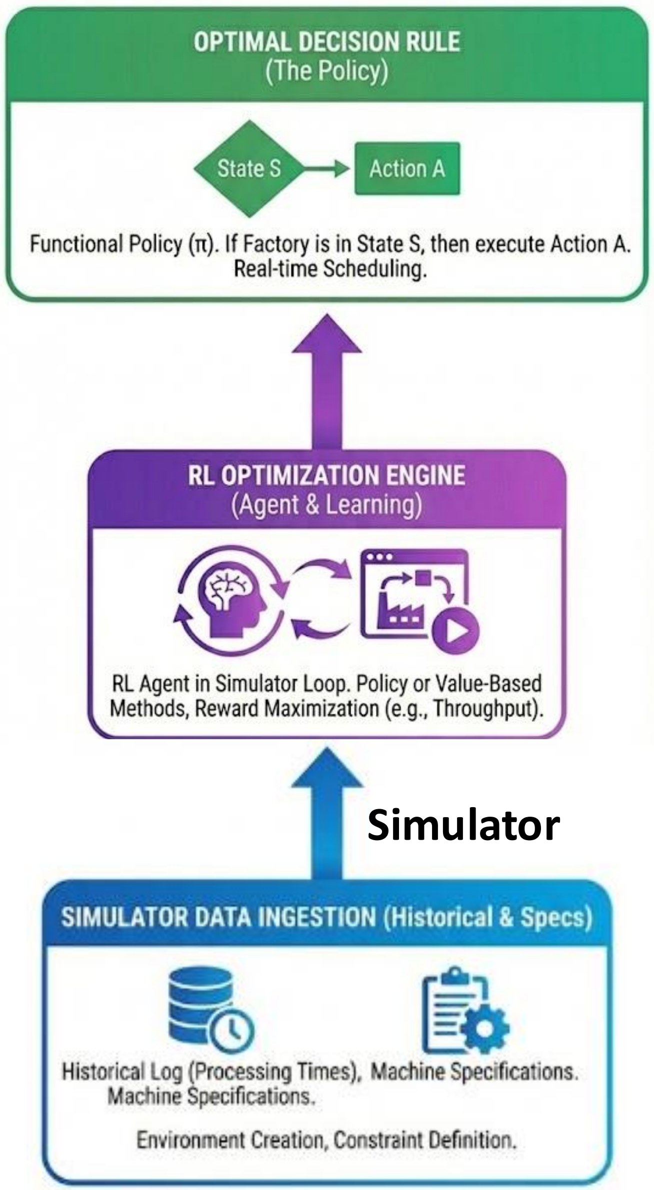
Online M.S. in AI

Production Optimization

- Production optimization helps enhance overall production efficiency by finding a better schedule.

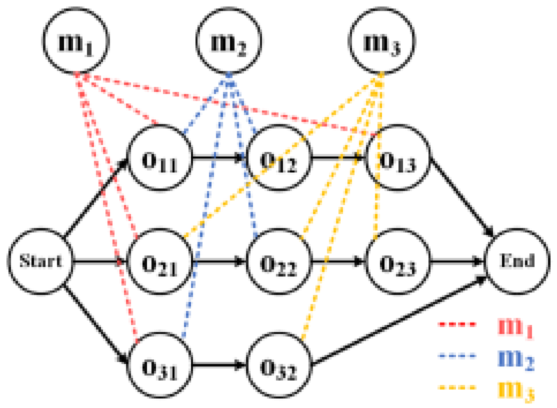
- **Goal**: determine the action (e.g., task to process, machine coordination) so that the throughput is maximized.
  - **Input**: a simulator of a production environment
  - **Output**: a learned decision rule over time

- **AI methods**: reinforcement learning
  - RL is the most suitable method to learn a sequential decision rule
  - It answers the question “what should we do” to provide prescriptive insights



Production Optimization – Example (Factory Level)

- **Problem Setting**: minimize the total processing time (makespan) in a general factory setting
  - **Jobs**: each job j_i (e.g., a car to manufacture) consists of a specific sequence of **operations** o_{ij} (e.g., welding)
  - **Machine**: for each operation, there is a set of eligible machines that can process it
    - E.g., there may be three machines that can do welding
  - **Processing time**: performing an operation o_{ij} on machine k take p_{ijk} amount of time



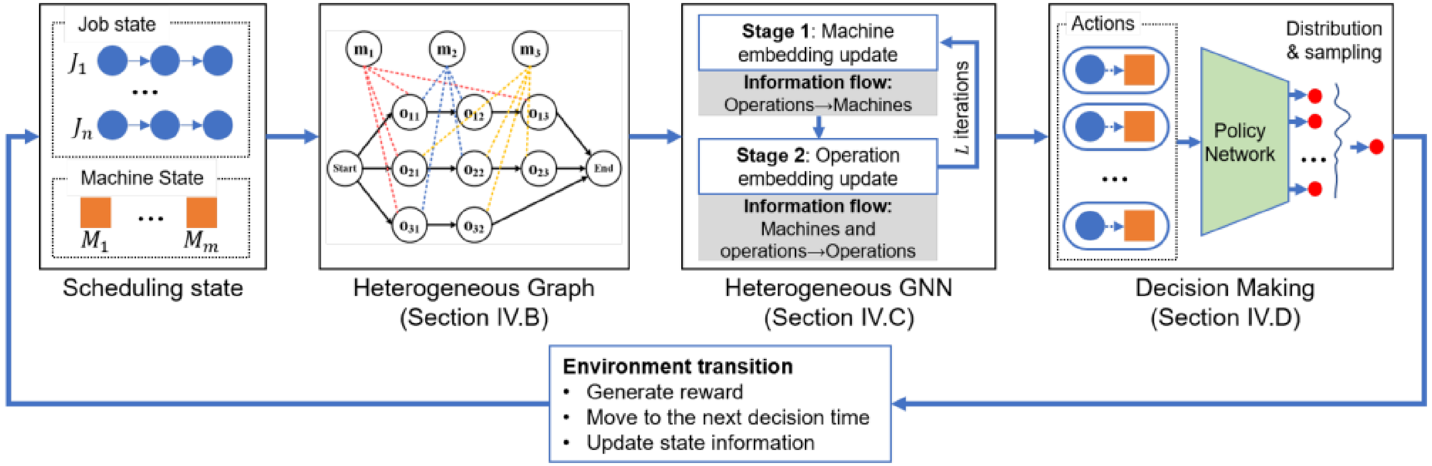
- The relationship between operations and machines forms a graph structure, where:
  - **Nodes** are operations o_{ij} and machine m_k
  - **Edges** are:
    1. Whether a machine can process an operation
    2. The sequence of operations in a job

Reference: Song, W., Chen, X., Li, Q., & Cao, Z. (2022). Flexible job-shop scheduling via graph neural network and deep reinforcement learning. *IEEE Transactions on Industrial Informatics*, *19*(2), 1600-1610.

Production Optimization – Example (Factory Level)

- **Sequential Decision:**
  - **State**: machine and job status captured by the graph at each timestamp
  - **Action**: machine assignment for each operation at each timestamp
  - **Reward**: provided when there's a decrease in the estimated time to finish all jobs

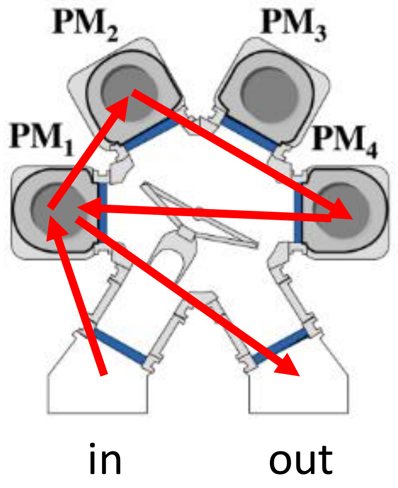
- **Design**:
  - Adapt **GNN** to capture the graph structure and create a state embedding for RL.
  - **Policy-based RL method with MLP policy network** to learn sequential decision rules.



Reference: Song, W., Chen, X., Li, Q., & Cao, Z. (2022). Flexible job-shop scheduling via graph neural network and deep reinforcement learning. *IEEE Transactions on Industrial Informatics*, *19*(2), 1600-1610.

Production Optimization – Example (Machine Level)

- **Problem Setting**: maximize the wafer per hour (throughput) in a semiconductor cluster tool
  - **Processing modules (PMs)**: there are several chambers in the cluster tool with different functionality
  - **Wafer**: wafers have a **recipe** that determines the order of PMs to go through (e.g., PM1 ➔PM2 ➔PM4 ➔PM1)
    - There is a **processing time** associated with each wafer and PM
  - **Robot**: connect multiple PMs that can move wafers between them (movement takes time)



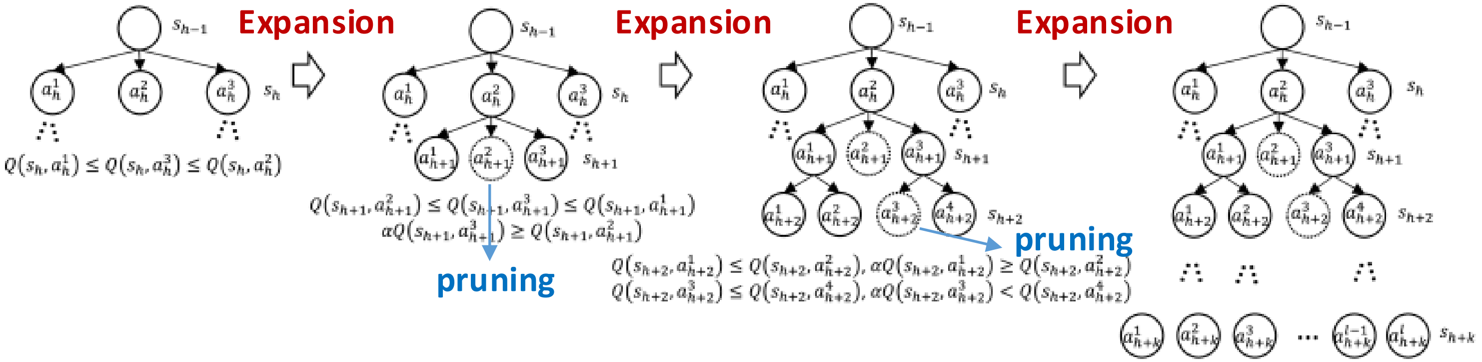
- **Characteristics**:
  - Search space is extremely large as there are multiple wafer recipes.
  - Deadlock is possible as wafers can re-enter a PM.

Reference: Kim, D., & Kim, H. J. (2025). Noncyclic Scheduling of Cluster Tools Using Deep Reinforcement Learning. *IEEE Transactions on Automation Science and Engineering*, *22*, 24009-24023.

Production Optimization – Example (Machine Level)

- **Sequential Decision**:
  - **State**: PM processing status, robot status, wafer recipe information
  - **Action**: robot movement (pick, place, wait)
  - **Reward**: granted when a wafer is completed or there is an expected throughput improvement

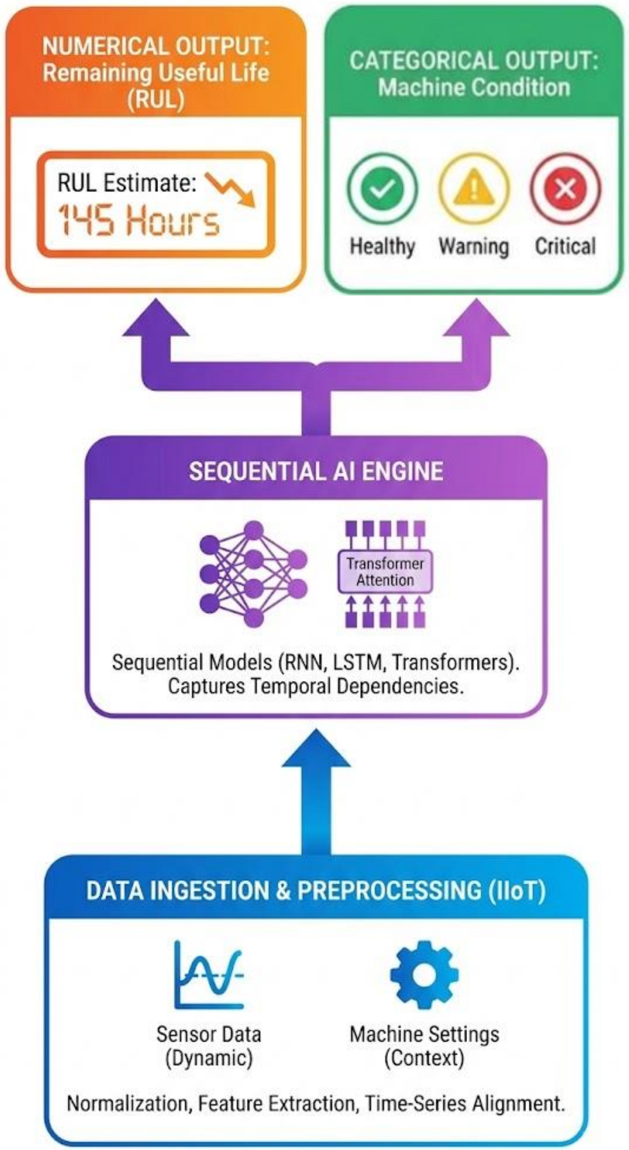
- **Design**: Value-based RL with adaptive search
  - **Expansion**: expand the search tree to look ahead for several steps to see how good an action is over a few future steps
  - **Pruning**: ignore actions the lead to low value or deadlock and only explore promising ones (based on Q value).



Reference: Kim, D., & Kim, H. J. (2025). Noncyclic Scheduling of Cluster Tools Using Deep Reinforcement Learning. *IEEE Transactions on Automation Science and Engineering*, *22*, 24009-24023.

Downtime Prediction

- During the manufacturing process, it is essential to ensure machines are in good condition.
- **Goal**: predict the remaining useful life based on real-time machine status.
  - **Input**: machine settings and sensor data over time (from IIoT)
  - **Output**: remaining life (numerical) or machine condition (categorical)
- **AI methods**: sequential models (e.g., RNN, LSTM, Transformers) for regression or classification

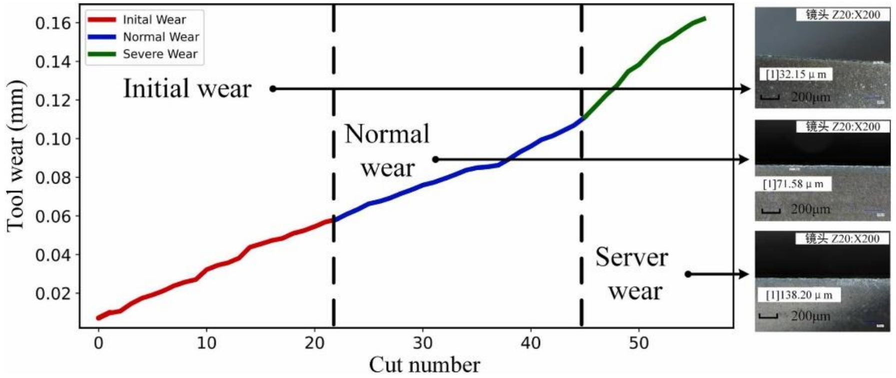


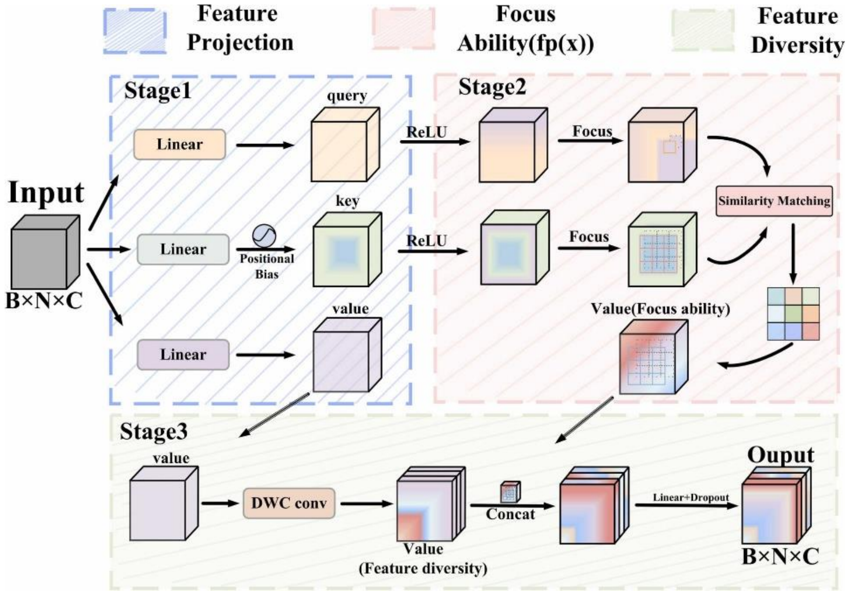
Online M.S. in AI

Reference: Aldrini, J., Chihi, I., & Sidhom, L. (2024). Fault diagnosis and self-healing for smart manufacturing: a review. *Journal of Intelligent Manufacturing*, *35*(6), 2441-2473.

Downtime Prediction – Example

- **Goal**: predict the physical degradation (wear value and state) of cutting tools in the Computer Numerical Control (CNC) machining production line.
- **Data**: PHM 2010 milling dataset, including
  - Sensor signals (including Cutting force, vibration, acoustic emission)
  - Tool setting (feed, speed, depth)
- **Key data characteristics**: long time series and the sensor signal can be affected by the tool setting under the same wear condition.
- **Design**: Extend a transformer model to allow:
  - **Context injection**: take machine settings as a separate input
  - **Feature alignment**: match the machine setting with sensor signals (through feature projection, focus ability, and feature diversity)

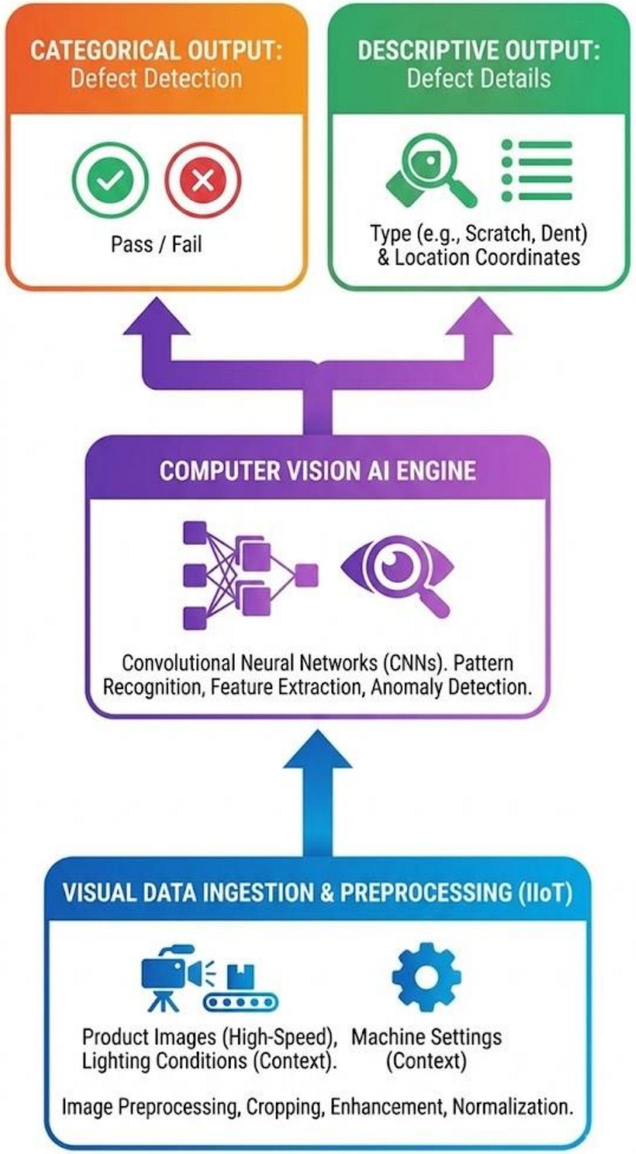




Reference: Hou, K., Li, R., Liu, X., Yue, C., Wang, Y., Liu, X., & Xia, W. (2025). Swin-fusion: An adaptive multi-source information fusion framework for enhanced tool wear monitoring. *Journal of Manufacturing Systems*, *79*, 435-454.

Defect Detection

- After a product is manufactured, we need to know whether they are defect or not.
- **Goal**: Classify each WIP or finished product into whether it is a defect or not
  - **Input**: product image from high-speed camera, machine settings (as context)
  - **Output**: defect classification (binary), defect details
- **AI methods**: CNN for anomaly detection



Reference: Aldrini, J., Chihi, I., & Sidhom, L. (2024). Fault diagnosis and self-healing for smart manufacturing: a review. *Journal of Intelligent Manufacturing*, *35*(6), 2441-2473.

Defect Detection – Example

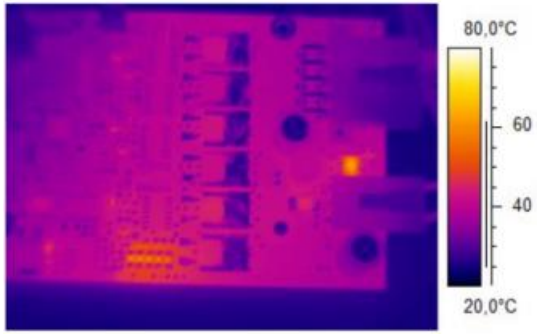
- **Goal**: detect both **visible** (surface) and **latent** (internal/thermal) soldering defects on Printed Circuit Board (PCB)

- **Data**: optical image (RGB) and thermal image from a custom-made scanning platform.

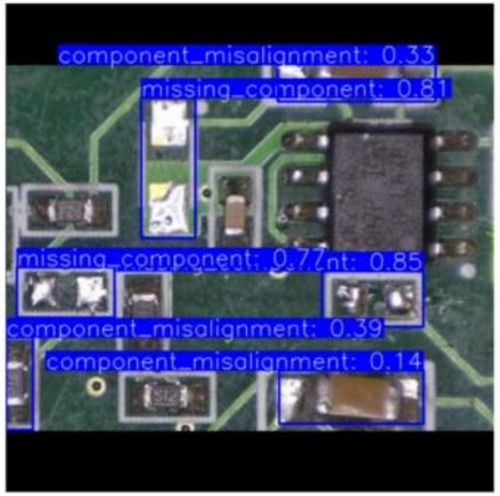
- **Data Characteristics**:
  - Optical data alone is "blind" to heat-related flaws
  - Defects usually come from the tiny details and precise geometry

- **Design**: A CNN-based model with
  - **Fusion** to jointly process optical and thermal images
  - **Hybrid Coordinate Attention Module** to focus on specific coordinates where features change rapidly (e.g., the edge of a solder ball)

Optical image



Thermal image



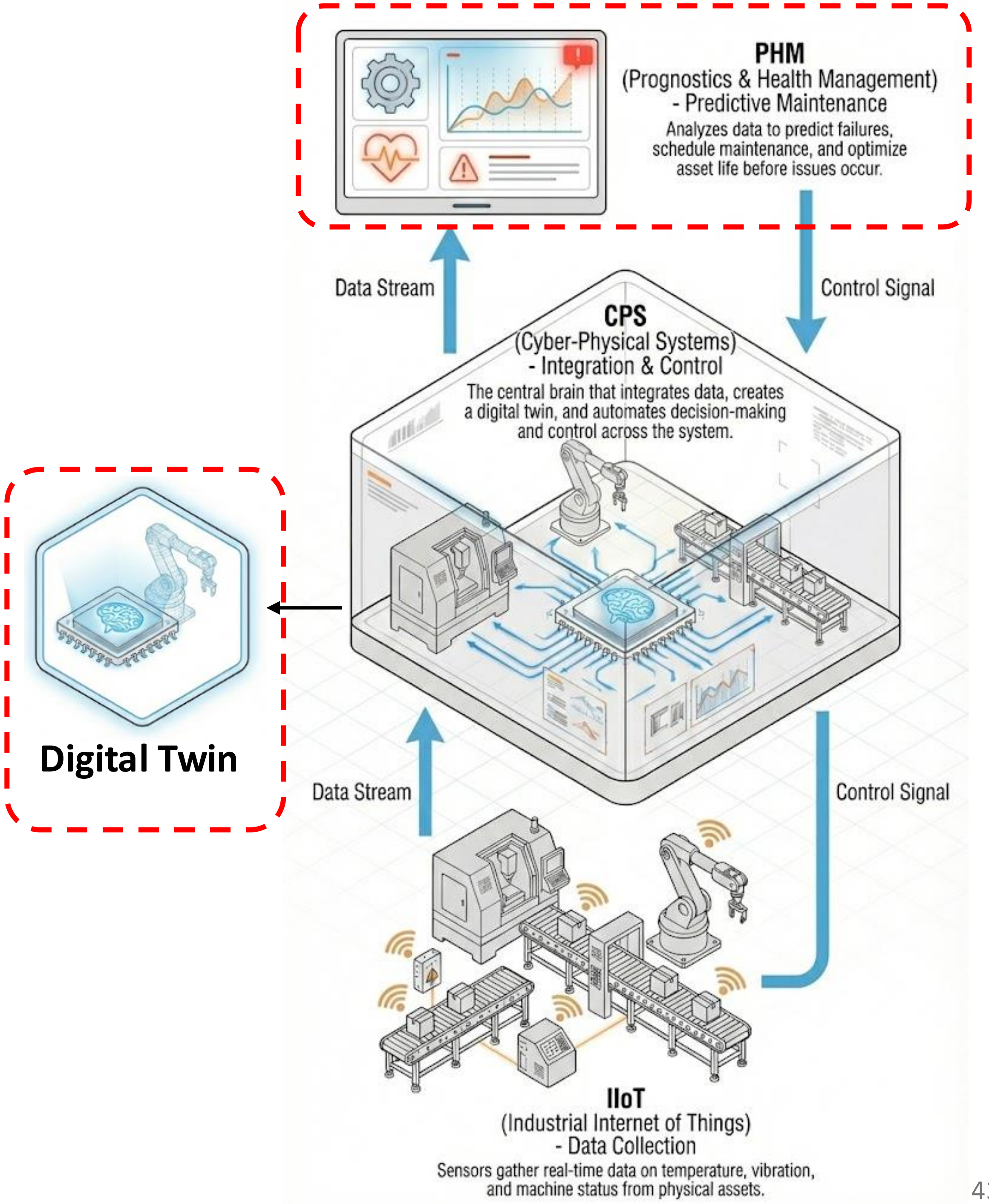
Defects on PCB

Reference: Diogo, T., Ramos, A., Pereira, F., Araújo, N., & Lopes, A. (2025). Automated detection and classification of soldering defects in printed circuit boards using deep learning and optical and thermal imaging. *Journal of Intelligent Manufacturing*, 1-24.

AI

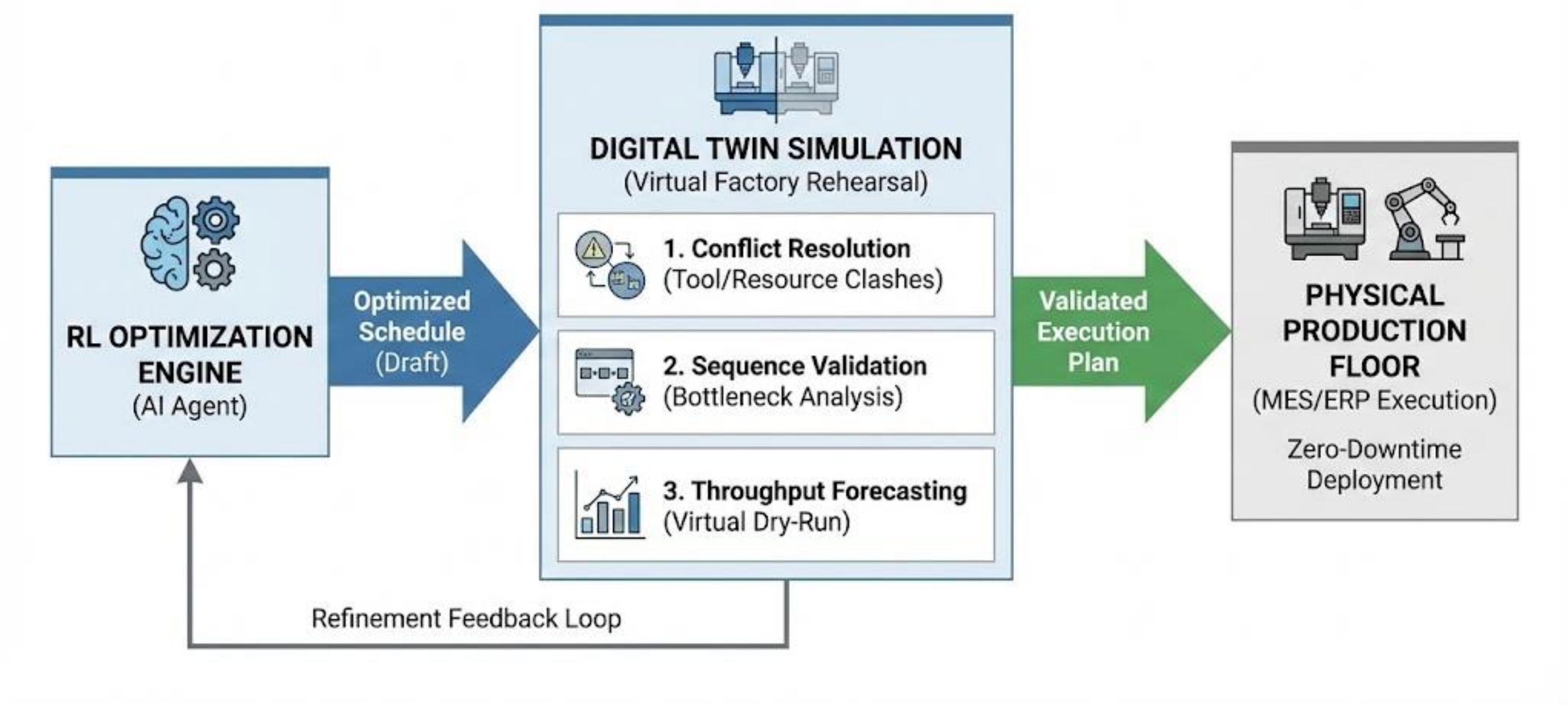
Step 4: Value Delivery

- The value of the two business problems is delivered in dinstinct way:
  - **Efficiency enhancement**: deploy the learned schedule on the digital twin to get acutal simulation result
  - **Failure management**: display the machine status in a dashboard in PHM



Value Delivery – Efficiency enhancement

- Once a schedule is optimized, the Digital Twin serves as a virtual proving ground to validate the plan before it is deployed to the physical factory floor.



Value Delivery – Failure Management

- PHM provides a dashboard to monitor the status of each machine comprehensively.

Image from https://www.integral-system.fr/products/solution-de-maintenance-predictive-pour-moteur-basee-sur-les-vibrations

A. **ISO 10818 Guideline:** maps raw vibration velocity against international mechanical health standards

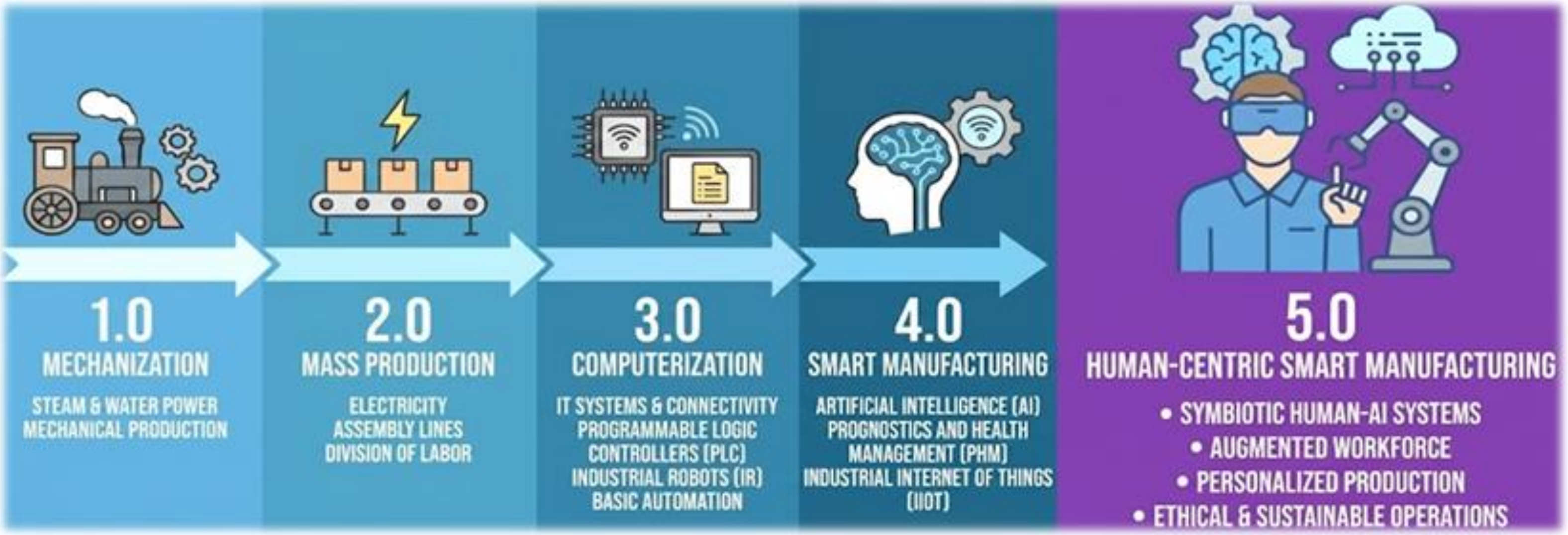
B. **Health Score (current and future):** shows the machine condition based on the downtime prediction analytics

C. **Skewness:** pinpoints specific faults (such as broken gear teeth or surface pitting) that can lead to product defect

Future Development

- In Industry 4.0 Smart manufacturing focuses on **system optimization** to improve efficiency, quality, and stability.

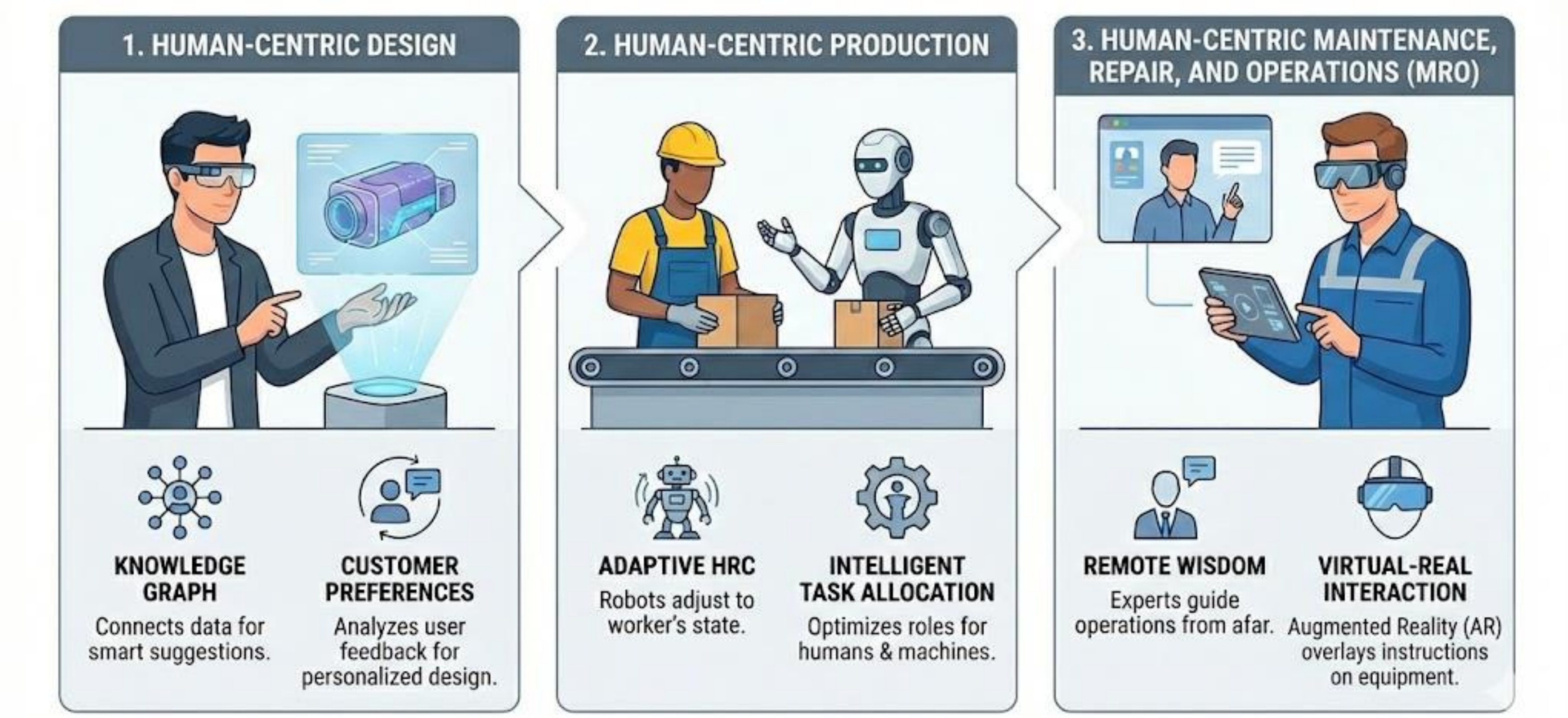
- It has started to evolve into Industry 5.0 by adding a **human-centric** layer to these technological advancements.
  - **Goal**: prioritize the **well-being of workers** rather than just focusing on system efficiency.



Reference: Zhang, C., Wang, Z., Zhou, G., Chang, F., Ma, D., Jing, Y & Zhao, D. (2023). Towards new-generation human-centric smart manufacturing in Industry 5.0: A systematic review. *Advanced Engineering Informatics*, *57*, 102121.

Future Development

- Human-centric Smart Manufacturing aims to reshape industrial processes through "X-intelligence" across three main stages:



Reference: Zhang, C., Wang, Z., Zhou, G., Chang, F., Ma, D., Jing, Y & Zhao, D. (2023). Towards new-generation human-centric smart manufacturing in Industry 5.0: A systematic review. *Advanced Engineering Informatics*, *57*, 102121.

Review Questions

- What are the key infrastructures in a smart factory in Industry 4.0?
- Why is production yield important in modern manufacturing settings like the semiconductor industry?
- How is a simulator different from a digital twin?
- What are the goals and common AI methods for the three major smart manufacturing analytics?