

Robotics, Automation, and Process Management for Industrial Operations

Review and Results from Real-World Use Cases Applying Machine Learning and Alternative Approaches

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Abstract—As industrial systems become increasingly complex, dynamic, and data-rich, organizations face growing pressure to enhance efficiency, flexibility, and decision-making through intelligent automation. This work examines how robotics, automation, and process management enable these transformations in modern industrial operations through data-driven and machine learning-based approaches. It first reviews the current state of research and industrial practice to establish a foundation for understanding technological and methodological developments in highly automated manufacturing environments. Building on this foundation, the article presents real-world industry use cases demonstrating how advanced analytics and machine learning improve material handling, robotics, intra-logistics automation, fleet management, and production operations. Particular attention is given to the operational deployment of machine learning, including machine learning operations (MLOps), and to the integration of engineering and management perspectives required to achieve robust and efficient manufacturing systems. The presented applications highlight improvements in system performance, operational efficiency, and decision support in complex industrial settings. By synthesizing practical insights and methodological advances, the article shows how these approaches can be transferred and extended across industries, contributing to more adaptive, intelligent, and resilient production systems.

Index Terms—Robotized picking and placing, travel time prediction, transportation system monitoring, rapid modeling, work-in-process level prediction, machine learning operations, semiconductor manufacturing, cosmetics industry

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I. INTRODUCTION

The successful coordination of value-adding transformation processes in manufacturing has always been a joint effort between operations management and engineering. This includes product design and development, as well as procurement, manufacturing, distribution, and sales processes [1], [2]. Therefore, both business and technical operations must be integrated through shared information systems [3] to enable efficient and effective production systems that reduce time and costs, increase quality, satisfy customer demands, and enable competitive advantages [4].

A fundamental approach to optimization is to focus on and depict the material, information, and cash flows of value and supply chains from a process perspective. This perspective highlights the partners, steps, interfaces, and transformations involved — from the supply of raw materials to the delivery of finished products to the end customer.

The increasing complexity, variability, and speed of modern industrial systems require tighter integration of management and engineering perspectives. Digitalization and machine learning (ML) have emerged as powerful enablers of this integration. They provide tools to extract actionable insights from complex and dynamic environments, bridging the gap between operational and information technology (IT). ML enables predictive maintenance, dynamic scheduling, adaptive control, and real-time decision support. When combined with advanced robotics, automation, and intralogistics, ML-driven approaches open new opportunities to increase throughput, reduce variability, and improve the robustness of industrial operations.

Equally important, process management provides the organizational and methodological framework to ensure that technological advancements align with business objectives and operational constraints. The interplay of machine learning, robotics, and management practices is particularly relevant for highly automated industries such as semiconductor manufacturing, intralogistics, and process industries, where variability, high product complexity, and strict quality requirements present unique challenges.

This work presents several engineering and management approaches that use digitalization, machine learning, and deep learning tools in the European research and development project AIMS5.0 (*Artificial Intelligence for Manufacturing Leading to Sustainability and Industry 5.0*).¹ It shows the improvements of these approaches along their respective transformation processes, as depicted in Fig. 1.

The paper begins with a section on state-of-the-art approaches in the literature and industry regarding individual aspects, such as robotics, automation, and process management — especially material handling, intralogistics, and production management. The subsequent section presents approaches beyond the state of the art as developed in the project AIMS5.0 and applied in industries ranging from cosmetics to semiconductor manufacturing. Finally, the approaches, benefits, and challenges are compared and generalized to other industries. Outlooks on their further development and application are also provided.

II. LITERATURE REVIEW

This section reviews the state of the art in key technological and methodological domains that enable intelligent industrial operations. The objective is to provide a structured overview of foundational concepts, established approaches, and recent developments in operations management, robotics and material handling, automation and intralogistics, and machine learning operations (MLOps). These domains jointly form the technological and organizational basis for modern data-driven manufacturing systems.

To ensure a consistent perspective, each subsection introduces the scope and role of the respective domain, outlines core methods and technologies, discusses industrial applications and challenges, and highlights current research trends. This structure enables a systematic comparison of existing approaches and provides the conceptual foundation for the industrial applications presented in the subsequent sections.

A. Operations Management

a) Scope and Role: Production and process management addresses the systematic planning, organization, and optimization of value-adding activities in manufacturing. Its primary objective is to align resources — including machines, materials, labor, and information — with production goals such as cost reduction, lead time minimization, quality assurance, and operational flexibility. As such, operations management provides the conceptual and methodological backbone of modern manufacturing systems, bridging engineering practices on the shop floor with managerial decision-making at the organizational level.

¹<https://aims50.eu/>

b) Core Methods and Technologies: A wide range of approaches has been developed to model, analyze, and improve production systems. Classical methods include deterministic and stochastic modeling, queueing theory, linear programming, and discrete-event simulation, which provide analytical insights into system performance and constraints. Complementary methodological frameworks such as *Lean Production* [5], *Quick Response Manufacturing* [6], and *Factory Physics* [2] emphasize waste reduction, flow efficiency, and quantitative understanding of production dynamics.

More recent approaches focus on rapid modeling techniques [7], [8], which enable fast and flexible analysis of production systems under uncertainty by representing processes as networks of queues. These approaches address limitations of detailed simulation models, particularly high data requirements and long computation times, while maintaining sufficient accuracy for decision support.

The increasing availability of industrial data and advances in digitalization have further extended operations management methods through machine learning techniques. These enable data-driven forecasting, anomaly detection, adaptive scheduling, and real-time decision support, complementing traditional analytical and simulation-based approaches and supporting more agile and intelligent production systems.

c) Industrial Applications and Challenges: Effective production and process management is critical for product quality, reducing costs, and improving customer satisfaction across industrial domains [9]. Industrial applications include integrated product and process control for sustainable manufacturing [10], quality management systems in semiconductor production [11], and quality function deployment for aligning customer requirements with production processes [12].

However, industrial production systems are characterized by inherent variability arising from process disruptions, equipment failures, and supply chain fluctuations [2], [13]. Managing this variability requires appropriate buffering strategies involving inventory, capacity, or lead time adjustments, often captured by trade-off models such as the operations management triangle [14], [13], [15]. Modeling the dynamic interaction of variability remains challenging, particularly in complex and highly automated environments where detailed simulation models may be costly and time-consuming to implement.

d) Research Trends and Outlook: Recent research increasingly focuses on digital transformation and intelligent manufacturing, integrating artificial intelligence, Internet of Things technologies, and data-driven decision-making into production management systems [16], [17], [18]. These developments aim to enhance responsiveness, improve system efficiency, and enable adaptive production control. Despite significant progress, challenges remain in modeling complex system dynamics, managing heterogeneous data sources, and integrating advanced analytics into operational workflows, motivating the development of the approaches presented in this work.

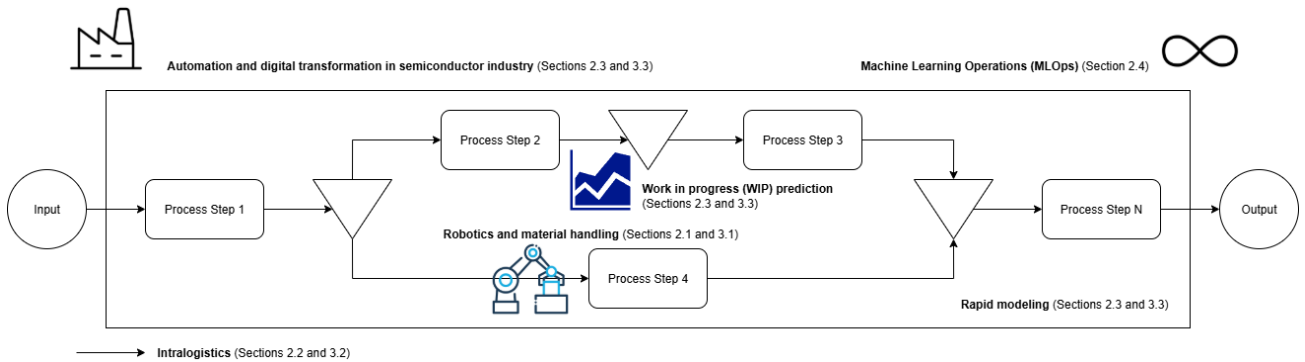


Fig. 1: Generic industrial transformation process and respective topics addressed in this article.

B. Robotics and Material Handling

a) Scope and Role: Material handling encompasses tasks such as intralogistics, machine tending, assembly line feeding, and warehouse operations. In the context of robotics, material handling refers to the use of autonomous or semi-autonomous robotic systems to move, manipulate, and organize materials within production and logistics environments [19]. Robotics is defined as the science and practice of designing, manufacturing, and applying robots [20].

Robotic material handling represents a subset of broader material handling equipment, which also includes conventional systems such as conveyors or palletizers [21], [22]. However, robotic solutions enable higher flexibility, adaptability, and automation, directly affecting throughput, quality, and operational safety. Consequently, robotic material handling has become a central component of modern manufacturing and logistics systems [21].

b) Core Methods and Technologies: Robotic material handling systems can be broadly categorized into mobile robots, robotic manipulators, and hybrid systems combining mobility and manipulation capabilities. Mobile robots transport materials across operational environments without being confined to fixed workspaces. These include automated guided vehicles (AGVs), autonomous mobile robots (AMRs), and unmanned aerial vehicles (UAVs). AGVs typically operate on predefined paths and execute repetitive tasks using programmed instructions with minimal human intervention [23], [24]. In contrast, AMRs navigate dynamically and make independent decisions based on environmental perception, enabling flexible operation in changing environments [23], [24]. UAVs extend material handling capabilities to aerial transport tasks, such as automated delivery of lightweight materials in construction environments [25], [26].

Robotic manipulators enable precise handling of objects and are widely used in machine tending and internal logistics applications [27]. Hybrid mobile manipulators combine transportation and manipulation capabilities by integrating robotic arms with mobile platforms, enabling flexible execution of complex tasks such as machine tending under uncertain conditions [28].

Recent developments further include collaborative robots designed for safe human–robot interaction in Industry 5.0 environments [19], soft robotic end-effectors for handling

delicate or deformable objects [29], and advanced perception and control technologies integrating vision systems, force sensing, motion planning, and multi-robot coordination.

c) Industrial Applications and Challenges: Robotic material handling systems are widely deployed in manufacturing plants, assembly lines, warehouses, and logistics facilities, where they support efficient transport of raw materials and finished goods between production stages. These systems improve operational efficiency, reduce manual labor requirements, and enhance workplace safety.

However, several challenges remain for industrial adoption. Handling complex or deformable objects requires advanced perception and control capabilities, while robust human–robot collaboration demands high safety standards and reliable interaction mechanisms. In addition, system integration, scalability, and performance limitations in dynamic environments continue to present technical and operational challenges.

d) Research Trends and Outlook: Current research focuses on increasing autonomy, adaptability, and intelligence in robotic material handling systems. Emerging directions include AI-driven perception and decision-making, improved manipulation of complex objects, enhanced human–robot collaboration, and more flexible mobile manipulation systems. Progress in robotics, materials science, and artificial intelligence is expected to further expand the capabilities of material handling systems and enable more adaptive and intelligent industrial operations.

C. Automation and Intralogistics

a) Scope and Role: Automation aims to improve efficiency, quality, safety, and cycle times in industrial production and logistics processes [30]. In the context of intralogistics, automation focuses on managing internal material flows, including handling and transportation tasks required to move loads between production resources. While handling involves storing, unpacking, or transferring goods over short distances, transportation covers longer-distance movements between locations such as storage systems and production tools. These functions are closely interconnected, particularly in highly automated environments such as semiconductor manufacturing, where Automated Material Handling Systems (AMHS) coordinate material flows across production facilities.

b) *Core Methods and Technologies:* Automation in intralogistics is commonly characterized by hierarchical control structures and levels of autonomy. A widely used classification distinguishes automation stages ranging from manual operation to fully autonomous systems [31], [32], alongside task levels covering execution, monitoring, control, and planning functions [33]. These classifications reflect a transition from centralized to decentralized decision-making in automated production environments.

In semiconductor manufacturing, automation technologies include automated process tools, standardized equipment interfaces, and integrated control architectures enabling automated transfer and transport operations [34], [35]. Modern high-volume fabrication facilities employ overhead transport (OHT) systems that enable fully automated wafer handling using standardized carriers such as Front Opening Unified Pods (FOUPs). Advanced system designs include unified rail layouts and buffer mechanisms that improve flexibility, throughput, and tool utilization [36], [37].

c) *Industrial Applications and Challenges:* Automated intralogistics systems are essential for maintaining high production efficiency, particularly in semiconductor fabrication facilities where equipment utilization and transport reliability directly affect operational performance. These systems support large-scale material flows, reduce manual intervention, and enable precise coordination between production scheduling and transport operations.

However, increasing system complexity introduces challenges related to planning, coordination, and control across multiple hierarchical levels. The integration of production management and material handling control requires standardized communication architectures and interoperable control systems [38], [39]. In addition, infrastructure costs, system scalability, and dynamic transport requirements may limit the economic efficiency of certain automation solutions, motivating the exploration of alternative technologies such as flexible floor-based vehicles.

d) *Research Trends and Outlook:* Current research focuses on increasing autonomy and intelligence in intralogistics systems through artificial intelligence and machine learning techniques [40]. These technologies enable decentralized decision-making, adaptive scheduling, and improved system optimization. At the same time, ongoing work addresses challenges related to system complexity, data integration, and robust control in highly automated production environments. Future developments are expected to further enhance flexibility, scalability, and economic efficiency in automated material flow systems.

D. Machine Learning Operations

a) *Scope and Role:* Machine Learning Operations (MLOps) integrates practices from software engineering, machine learning, and data engineering to manage the lifecycle of machine learning systems in production environments [41]. In industrial manufacturing, MLOps supports the deployment, monitoring, and maintenance of data-driven models, enabling reliable and scalable use of machine learning for tasks such as

machine vision, predictive analytics, and process optimization. Its primary objectives include rapid model iteration, automated deployment, and continuous performance monitoring.

b) *Core Methods and Technologies:* MLOps encompasses a set of processes covering data collection and preprocessing, model training and evaluation, deployment, and monitoring throughout the model lifecycle [42]. Similar to DevOps practices, MLOps employs Continuous Integration and Continuous Delivery (CI/CD) pipelines to enable automated updates and seamless deployment of machine learning models.

Key technical aspects include model versioning, performance evaluation, and retraining strategies to ensure model adaptability to changing operational conditions [43]. In industrial settings, MLOps systems must address constraints related to computational resources, real-time data processing, and integration of heterogeneous data sources, which pose additional challenges compared to traditional software environments.

c) *Industrial Applications and Challenges:* Industrial adoption of MLOps enables standardized and scalable management of machine learning systems across diverse application domains, including manufacturing, robotics, and digital technology systems [42]. However, implementation requires significant investment in infrastructure and specialized expertise, which may limit adoption in risk-sensitive production environments.

Major challenges include integrating heterogeneous data sources, ensuring model reliability in safety-critical systems, and maintaining performance under changing process conditions. Furthermore, the setup of fully operational MLOps pipelines requires substantial organizational and technical effort, particularly in established industrial environments with legacy systems.

d) *Research Trends and Outlook:* Current research focuses on standardizing MLOps practices, improving data pipeline integration, and developing scalable frameworks for industrial machine learning deployment. As machine learning applications continue to expand in manufacturing, MLOps is expected to play an increasingly important role in enabling reliable and maintainable AI-driven systems. Although adoption is expected to be gradual, the growing maturity of MLOps technologies supports their integration into industrial operations and motivates the development of practical deployment strategies.

III. INDUSTRIAL APPLICATIONS

In this section, several real-world applications are demonstrated, especially in the fields of robotics and material handling in the process industry, and concerning automation, intralogistics, and production management in semiconductor manufacturing.

A. Operations Management

1) *Use Case: Production Optimization in Semiconductor Manufacturing at Infineon Dresden:*

TABLE I
CLASSIFICATION MATRIX CONNECTING AUTOMATION STAGES AND TASK LEVELS IN INTRALOGISTICS (ADAPTED FROM [33]).

Task level	Automation Stages					
	Stage 0	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
Overall system planning (Level 4)	Manual decision making in overall system planning	Decision support system in overall system planning	Partly centralized decision making in overall system planning	Centralized decision making in overall system planning	Partly decentralized decision making in overall system planning	Decentralized decision making in overall system planning
Overall system control (Level 3)	Manual decision making in overall system control	Decision support system in overall system control	Partly centralized decision making in overall system control	Centralized decision making in overall system control	Partly decentralized decision making in overall system control	Decentralized decision making in overall system control
Process control and monitoring (Level 2)	Manual decision making in process control and monitoring	Decision support system in process control and monitoring	Partly centralized decision making in process control and monitoring	Centralized decision making in process control and monitoring	Partly decentralized decision making in process control and monitoring	Decentralized decision making in process control and monitoring
Device control and information processing (Level 1)	Manual search and transfer of information on demand	Assisted search and transfer of information on demand	Assisted and partly self-contained information acquisition and processing	Fully self-contained information acquisition, generation of information and interaction with central system	Fully self-contained information acquisition, generation of information and partly interaction with other system elements	Fully self-contained information acquisition, generation of information and interaction with other system elements
System execution and real time control (Level 0 and 1)	Manual execution in static environment	Manual assisted execution in static environment	Assisted and partly self-contained execution in static environment	Partly self-contained execution in infrequently changing environment	Fully self-contained execution in dynamic environment	Fully self-contained execution in complex and dynamic environment



Fig. 2: Inside the fully automated 200mm line at Infineon Dresden.

a) Industrial Context and Problem Definition: Semiconductor manufacturing is characterized by high capital investment, strict quality requirements, and complex production processes. Efficient production and process management are therefore critical to ensure product quality, reduce costs, and maintain competitiveness. The Infineon Dresden wafer fabrication facility operates a highly automated 200 mm production line, established in 1995 and later transformed from a high-volume memory facility into a high-mix, high-volume logic factory. The line achieves an automation level of approximately 93%, enabling flexible production of hundreds of products (Fig. 2).

The facility relies on advanced automation, digitalization, and lean production principles to manage variability, optimize resource utilization, and ensure stable production performance. Increasing system complexity and data availability motivate the use of advanced analytics and machine learning methods to improve production planning, process control, and decision support.

b) Approach / Methodology: Production optimization at Infineon Dresden combines several complementary approaches. Factory automation integrates robotics, machine learning, and data analytics for real-time monitoring and



Fig. 3: IoT Technologies Used to Move Production to Industry 5.0.

process optimization. Digitalization initiatives based on Industry 4.0 concepts enable the integration of cyber-physical systems, predictive analytics, and Internet of Things technologies to support data-driven decision-making (Fig. 3). Future developments aim to further integrate AI technologies and human-machine collaboration in Industry 5.0 environments [44].

Operational performance is further supported by lean manufacturing principles [45], Statistical Process Control (SPC), Advanced Process Control (APC), and Fault Detection Control (FDC). These methods enable continuous process monitoring, reduction of variability, and early detection of anomalies. Machine learning techniques complement these approaches by enabling predictive analytics and adaptive process optimization.

c) Experimental Setup / Implementation: The production environment is supported by a Manufacturing Execution System (MES) that serves as a central data infrastructure, collecting more than one billion sensor readings per day. The MES integrates data from process monitoring systems, equipment sensors, and production workflows, providing a foundation for advanced analytics and machine learning applications.

Process monitoring, quality control, and operational decision-making are implemented through integrated SPC, APC, and FDC systems combined with machine learning methods. The production environment also incorporates health and safety measures, including enclosed fabrication systems

and automated processes to minimize workplace risks [46], [47].

d) Results and Insights: The integration of automation, digitalization, and process control enables stable production performance, improved quality, and increased operational efficiency. Data-driven monitoring allows early detection of process deviations and supports continuous process improvement. The large-scale data infrastructure provides opportunities for advanced machine learning applications, enabling predictive maintenance, adaptive production planning, and improved decision support.

e) Implications and Transferability: This case demonstrates how the integration of automation, digitalization, and data-driven process management enables efficient operation of highly complex production systems. The combination of lean production, advanced process control, and machine learning provides a transferable framework for managing variability and improving operational performance in other highly automated manufacturing environments.

2) *Use Case: Rapid Modeling to Identify Process Variability:*

a) Industrial Context and Problem Definition: Efficient utilization of production capacity is essential in semiconductor manufacturing due to high investment costs and long scale-up timelines. In 2023, Infineon Dresden observed increasing work-in-process (WIP) levels and long waiting times in the production of wafers based on a specific power technology (PTX). The issue was particularly pronounced at a workstation referred to as Y, motivating a study to determine whether performance limitations were caused by insufficient capacity or high process variability.

b) Approach / Methodology: A rapid modeling approach based on queueing theory was implemented using the IMPAQT software framework [48]. Rapid modeling enables efficient simulation of production dynamics and evaluation of key performance indicators such as flow time, WIP, and utilization.

The analysis focused on workstation Y and an upstream workstation X to capture the impact of upstream variability. Since process and interarrival times were not exponentially distributed, the system was modeled as a G/G/m queue. Waiting times were estimated using Whitt's approximation [49], and equipment failure effects were incorporated following Segal and Whitt [50].

c) Experimental Setup / Implementation: Production data from 2023 were used to parameterize the model, including process times, arrival rates, and equipment availability. Only productive lots were considered. The simulation was conducted on a monthly basis to account for the expansion of workstation Y from one to two machines during the observation period.

d) Results and Insights: The analysis revealed high variability in process times and unscheduled downtime, particularly at workstation Y. This variability caused extended idle periods and long flow times of nearly two days per wafer.

Compared with theoretical capacity specifications, simulation results showed unexpected utilization patterns (Fig. 4). Utilization was higher during low throughput periods and lower during high throughput periods, indicating that perfor-

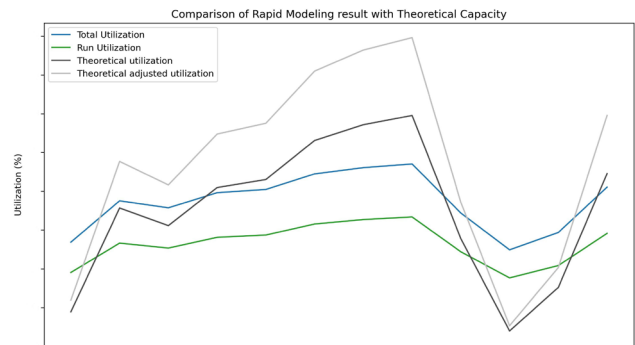


Fig. 4: Comparison of theoretical workstation Y utilization (with PTX technology lots) with rapid model results

mance limitations were primarily driven by variability rather than insufficient capacity.

Workstation Y was also more sensitive to demand fluctuations than workstation X, highlighting its role as a major source of production instability.

e) Implications and Transferability: Rapid modeling provides an efficient analytical tool for identifying variability-driven bottlenecks in complex production systems. The approach enables targeted improvement measures without requiring detailed simulation models and is transferable to other manufacturing environments facing similar capacity and variability challenges.

3) *Use Case: Prediction of Work-in-Process Levels Using Machine Learning:*

a) Industrial Context and Problem Definition: Factory simulations are widely used in semiconductor manufacturing for forecasting material flows and supporting capacity planning. However, existing simulations typically operate on daily or weekly horizons and do not provide sufficiently granular predictions for shop-floor decision-making. Accurate short-term forecasts of work-in-process (WIP) levels would enable operators to anticipate bottlenecks, balance workloads, and respond to production variability.

b) Approach / Methodology: The proposed solution applies machine learning methods for ultra-short-term forecasting of WIP levels based on real-time production data. The prediction task is formulated as a time-series regression problem. After data preprocessing following established guidelines [51], [52], multiple models including SARIMAX, XGBoost, LSTM, and CNN were evaluated [53], [54], [55].

An automated workflow was implemented within the Python ecosystem, covering data preprocessing, model training, hyperparameter optimization, and evaluation. Model performance was assessed using RMSE, MAE, and R^2 . Explainable AI methods such as SHAP values were applied to enhance interpretability and support human-AI interaction [56], [57].

c) Experimental Setup / Implementation: The models were trained using historical production data and evaluated in collaboration with factory experts. Visualization tools based on Plotly and Jupyter were developed to present predictions

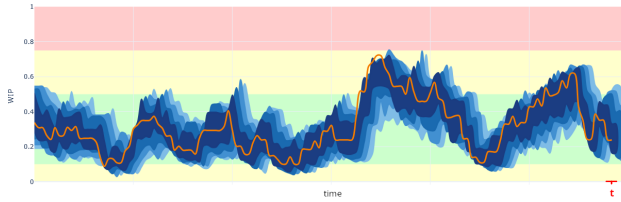


Fig. 5: Visualisation of WIP-development (orange) up to time t (red), alongside the corresponding forecast from $WIP_{t+0:30h}$ to $WIP_{t+2:00h}$ (blue with increasing brightness) at a confidence interval of 90% per forecast

and explanations to operators (Fig. 5, Fig. 6). Behavioral experiments measured user acceptance using the Weight on Advice (WOA) metric.

$$WOA = \frac{(\text{Initial Human Prediction} - \text{Adjusted Human Prediction})}{(\text{Initial Human Prediction} - \text{AI Prediction})}$$

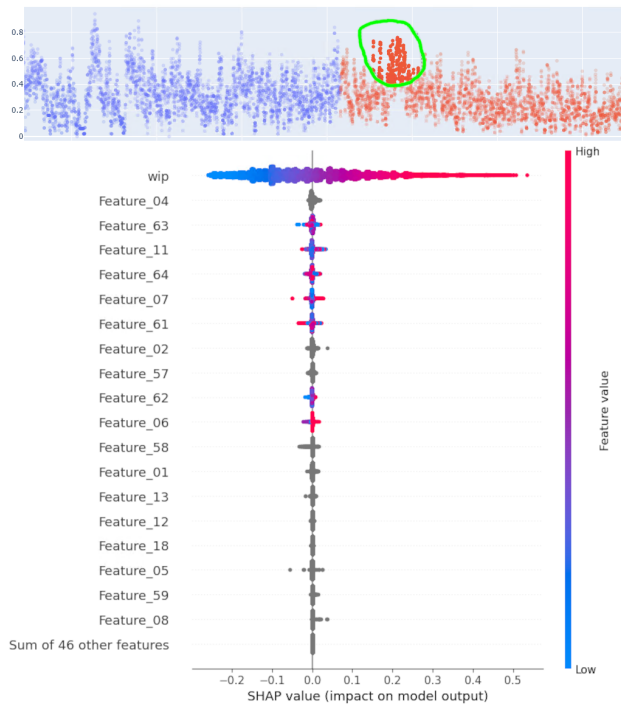


Fig. 6: Interactive dashboard-visualisation of the WIPprediction (red) and the SHAP-values (below) for selected data-points (green)

d) Results and Insights: The best-performing model (XGBoost) achieved an RMSE of 0.1035, MAE of 0.0813, and $R^2 = 0.5442$ for a prediction horizon of two hours. Although predictive accuracy remains limited, the results demonstrate the feasibility of short-term WIP forecasting and highlight the importance of data quality and feature selection.

Behavioral experiments ($N = 71$) showed that users relied more strongly on AI predictions when no explanations were provided ($WOA = 0.63$) than when explanations were included

($WOA = 0.58$), indicating that transparency influences trust and decision behavior.

e) Implications and Transferability: Machine learning-based WIP forecasting provides a promising approach for supporting operational decision-making in highly automated production environments. The integration of predictive models with explainable AI and human-AI interaction concepts supports practical adoption and offers transferable insights for decision-support systems in complex industrial settings.

B. Intralogistics

1) Use Case: Predicting Travel Times of AMR fleets:

a) Industrial Context and Problem Definition: This use case considers a fleet of free-ranging Automated Mobile Robots (AMRs) operating in a semiconductor fabrication environment. The robots transport carriers between input/output stations, storage areas, and production tools, and are coordinated by a fleet management system responsible for task assignment, routing, and congestion handling.

Fleet management in such environments involves highly interdependent decisions under dynamic conditions. Task allocation, route planning, and prioritization must be continuously updated to ensure efficient and collision-free operation. Semiconductor fabrication facilities operate under strict production schedules, where transport delays can lead to costly tool idle times and reduced throughput. Consequently, accurate prediction of AMR travel times is essential for maintaining operational efficiency.

Conventional travel time estimation methods based on average velocities or historical data provide limited accuracy, as they do not sufficiently account for real-time system conditions such as congestion or routing conflicts. These limitations motivate the development of data-driven prediction approaches that incorporate dynamic fleet interactions.

b) Approach / Methodology: A supervised learning approach is proposed to predict AMR travel times based on historical transportation data. A log file parser extracts structured input-output pairs from system logs, where input features describe the system state at a given time, including robot locations and destinations, while the target variable represents the observed travel time.

The prediction task is formulated as a regression problem that approximates the mapping from system state to expected travel time. The methodology incorporates both intermediate waypoints and final destinations to capture routing conflicts occurring during transport operations. The resulting model is integrated into the fleet management system to provide real-time predictions and can be periodically retrained using newly collected data.

c) Experimental Setup / Implementation: Training data were generated from several months of historical transportation logs in environments with medium-complexity layouts. The dataset included information on robot locations, destinations, and system states at corresponding timestamps. Various model configurations were evaluated, with a multilayer perceptron (MLP) achieving the best performance.

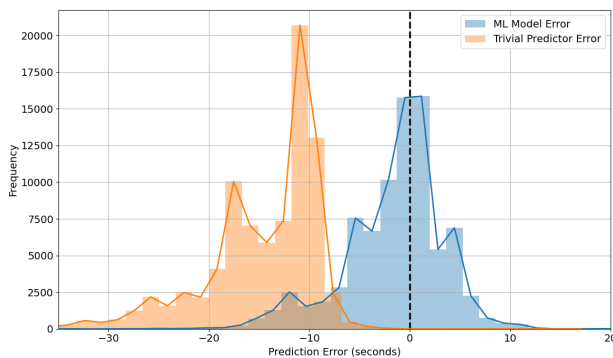


Fig. 7: Error distribution for travel time prediction with two different estimators

The model was deployed within the fleet management framework to estimate travel times dynamically and support task assignment and routing decisions.

d) Results and Insights: The trained model achieved a mean absolute error of approximately 3.7 seconds and an R^2 value of 0.82 on test data. Compared to a baseline estimator based on average speed, the prediction error was reduced from approximately 14.7 seconds.

The error distribution shown in Fig. 7 demonstrates that heuristic approaches systematically underestimate travel times, whereas the learned model captures congestion effects and fleet interactions more accurately.

Model performance was found to depend on data quality, layout characteristics, and traffic stability. High predictive accuracy was achieved in controlled environments with stable operating conditions.

e) Implications and Transferability: The results demonstrate that data-driven travel time prediction can significantly improve fleet management performance in automated intralogistics systems. The approach supports more efficient task allocation and routing decisions and can be transferred to other automated transport systems operating in dynamic industrial environments. Future work will investigate scalability to larger fleets, more complex layouts, and enhanced feature representations.

2) Use Case: Monitoring of Automated Material Handling Systems (AMHS):

a) Industrial Context and Problem Definition: Efficient operation of Automated Material Handling Systems (AMHS) is critical for semiconductor fabrication facilities, where reliable material transport directly affects production efficiency and tool utilization. Preventing AMHS downtime requires continuous monitoring of system components to detect malfunctions and initiate maintenance actions.

Condition monitoring typically relies on industrial sensor systems, which provide high-quality measurements but are costly to acquire and operate. This motivates the investigation of alternative low-cost sensing solutions. In particular, the suitability of consumer-grade sensors, such as those integrated into mobile devices, for monitoring AMHS components is evaluated.

Previous work has demonstrated the effectiveness of sensor-based condition monitoring for industrial systems [58], while highlighting the associated implementation costs [59]. Consumer devices equipped with embedded sensors have been successfully applied in domains such as healthcare and traffic monitoring [60], although their performance may be limited compared to industrial equipment [61]. Their applicability in semiconductor intralogistics environments remains largely unexplored.

b) Approach / Methodology: A modular sensor platform was developed to compare different sensing technologies for AMHS condition monitoring. The platform integrates multiple sensor systems, including an Android mobile phone, two single-board computers (Arduino and Raspberry Pi), and a professional industrial sensor system (Fig. 8). The collected acceleration data are analyzed in both time and frequency domains to assess measurement accuracy and reliability.

c) Experimental Setup / Implementation: The platform was tested in representative scenarios, including overhead hoist transportation (OHT) movements, automated guided vehicle (AGV) transport, and controlled experiments using a calibrated shaker. Sensor characteristics are summarized in Table II.

Experiments evaluated sensor performance under controlled oscillations (Fig. 9), shock events (Fig. 10), and real AMHS movements (Fig. 11). A lightweight Android application was developed to record and preprocess sensor data (Fig. 12), enabling deployment in cleanroom environments.

The platform was subsequently applied in operational tests involving FOUP transport via OHT systems and AGVs. Additional experiments combined acceleration and audio data to improve event detection through data fusion.

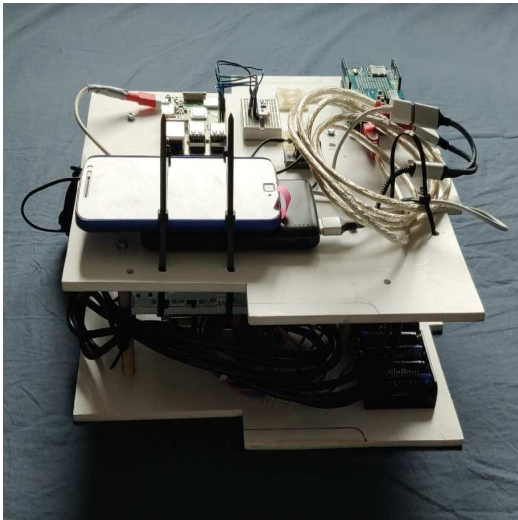
d) Results and Insights: The experiments showed that consumer-grade sensors can capture key dynamic events such as oscillations and shock loads with reasonable accuracy. The Android mobile phone provided measurement values comparable to the professional system in several scenarios, while the Raspberry Pi and Arduino sensors showed limitations in reliability and accuracy.

All sensors detected shock events with reproducible response times (Fig. 10), although frequency detection was limited by the sampling rate of mobile devices. During AGV operation, only the mobile phone and professional system produced plausible measurements (Fig. 11).

Operational tests in the cleanroom environment revealed no unexpected mechanical loads during transport operations (Fig. 13). Additional experiments demonstrated that combining acceleration and audio data enables detection of specific AMHS events such as FOUP door locking and hoisting processes (Fig. 14, Fig. 15).

e) Implications and Transferability: The results indicate that low-cost consumer sensors can provide useful monitoring capabilities for AMHS condition monitoring, particularly when combined with data fusion techniques. Although limitations remain in measurement precision and sampling rates, the approach offers a cost-effective alternative to traditional industrial sensing solutions.

The developed sensor platform and analysis workflow provide a transferable framework for condition monitoring in



(a) Sensor platform

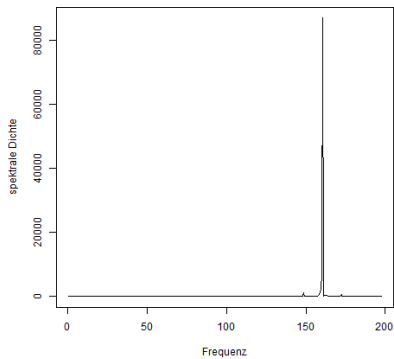


(b) Sensor platform in a FOUP

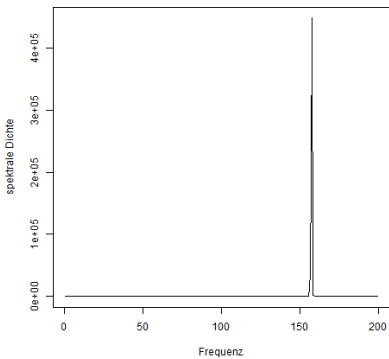
Fig. 8: Sensor platform with different sensor systems

TABLE II
APPLIED SENSOR SYSTEMS AND THEIR SPECIFICATIONS; $g \approx 9,81 \text{ m/s}^2$; LSB: LEAST SIGNIFICANT BIT

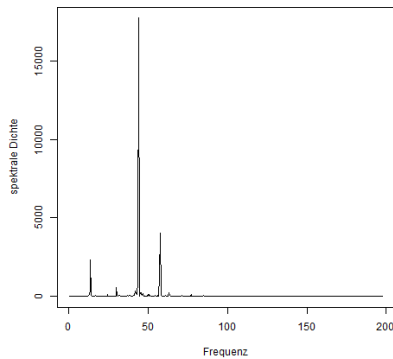
Specification	Professional System	Raspberry Pi	Mobile Phone
Range	+4 g, -1 g	$\pm 4 \text{ g}$	$\pm 4 \text{ g}$
Resolution	12 bits	10 bits	10 bits
Accuracy	1 %	128 LSB/g	128 LSB/g
Measuring Rate	continuous (analog)	3200 Hz	1600 Hz
Sampling Rate	1000 Hz	4040 Hz	$\approx 100 \text{ Hz}$



(a) Industrial system



(b) Raspberry Pi



(c) Mobile phone

Fig. 9: Periodograms of the sensor systems' data when triggered with 159.2 Hz

automated transport systems and support further research on scalable and cost-efficient monitoring solutions for industrial environments.

C. Robotized Picking and Placing in the Process Industry

a) Industrial Context and Problem Definition: In industrial process automation, AI solutions increasingly support

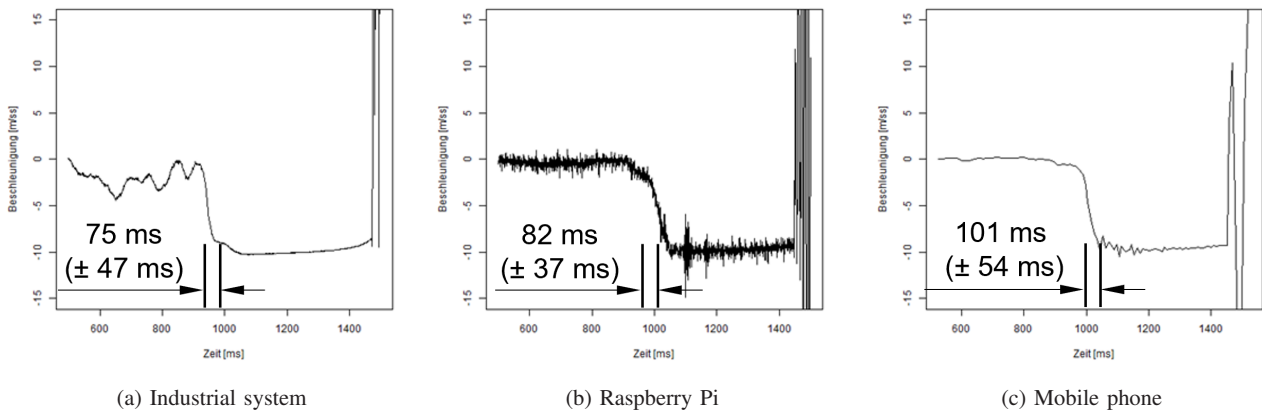


Fig. 10: Time series of the sensor systems’ data recording a shock event;

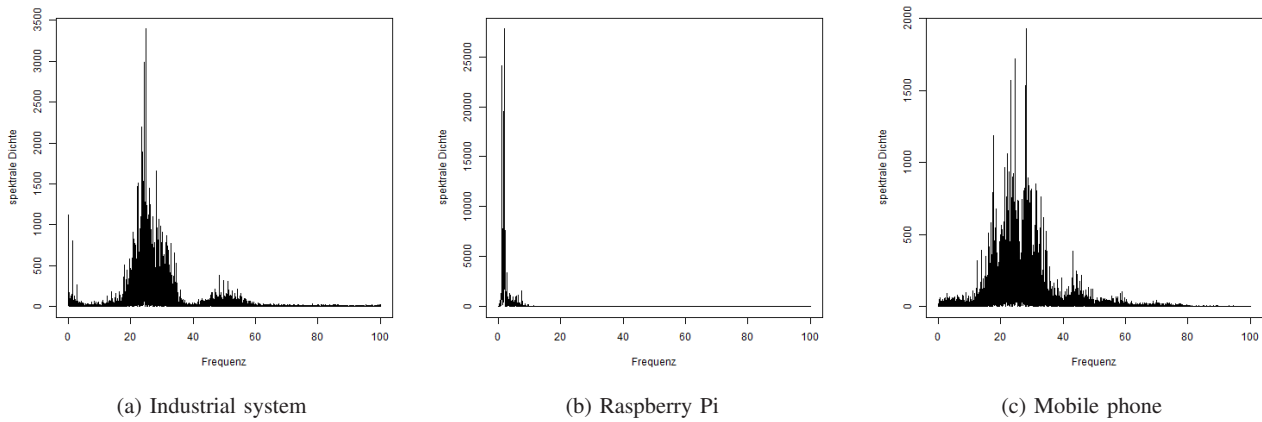


Fig. 11: Periodograms of the sensor systems’ data on a random AGV movement

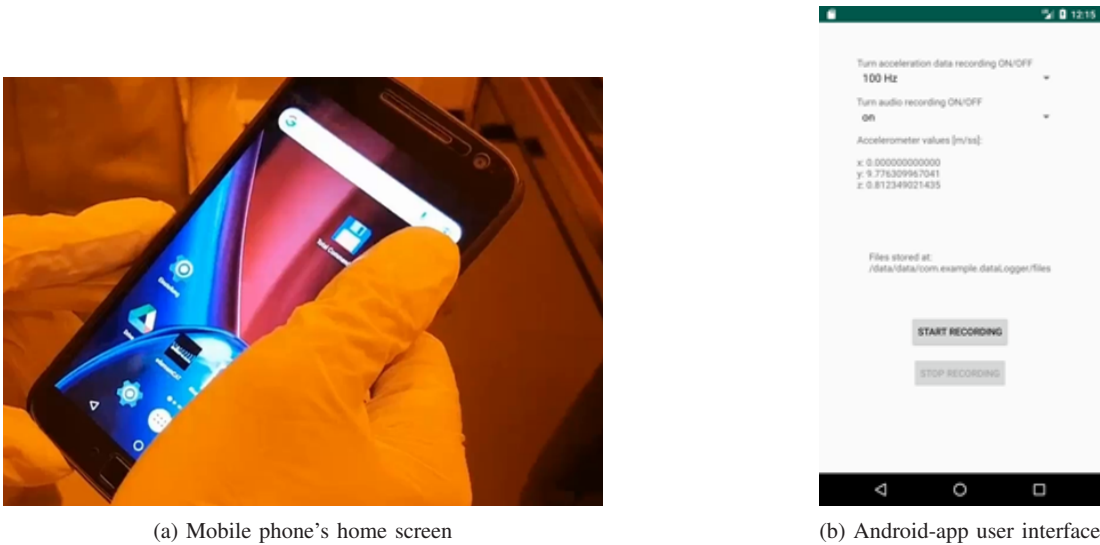
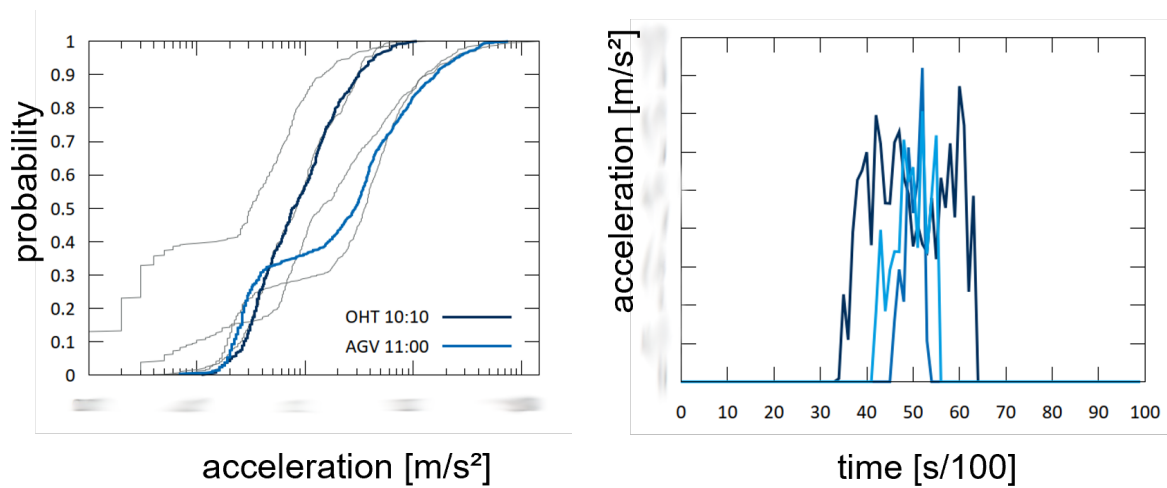


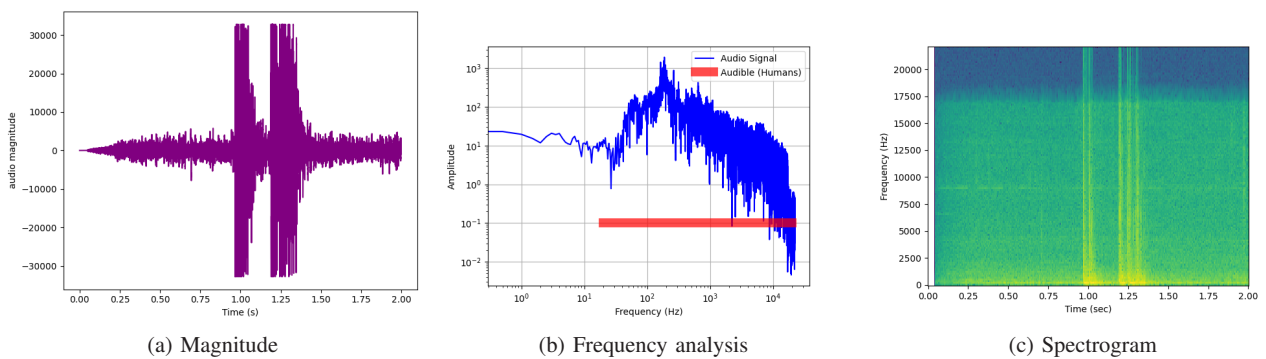
Fig. 12: Android mobile phone with app for sensor data recording



(a) Cumulative distribution function of recorded acceleration values

(b) Time series of recorded acceleration values

Fig. 13: Acceleration values recorded by the sensor platform applied in a FOUP carried by an OHT-vehicle (darker blue) and an AGV (brighter blue); precise values blurred for reasons of confidentiality

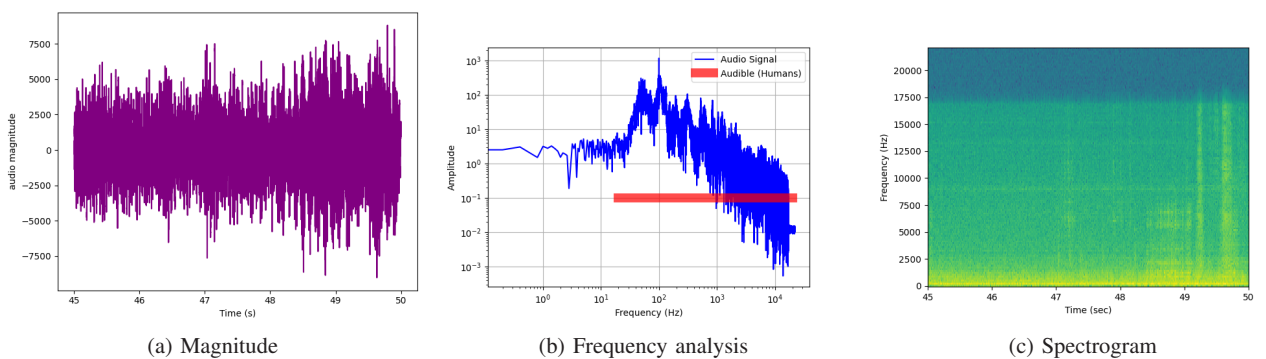


(a) Magnitude

(b) Frequency analysis

(c) Spectrogram

Fig. 14: Sensor data values while opening a FOUP's door



(a) Magnitude

(b) Frequency analysis

(c) Spectrogram

Fig. 15: Sensor data values while hoisting a FOUP by an OHT-vehicle

flexible and adaptable operations, often in confined and dynamic environments where robots must operate safely and efficiently alongside humans. A core task in this context is object picking and placement [62], which underpins assembly lines as well as packaging and material handling use cases [63]. Modern robotic solutions combine manipulators with

machine vision and advanced control to perform these tasks with high precision and speed [64].

Industrial deployments face recurring challenges: (i) robust operation under uncertainty, including varying object shapes, sizes, and poses [65], (ii) frequent task and product changes that require rapid reconfiguration with minimal human inter-

vention, and (iii) safe operation near humans through effective human intention detection and responsive motion planning [66]. Reinforcement Learning (RL) and related machine learning methods offer mechanisms for adaptive behavior, enabling robots to learn strategies in simulation and transfer them to real-world environments, improving safety and efficiency under changing conditions.

b) Approach / Methodology: The proposed approach combines modular robotic manipulation, machine vision, and learning-based control to automate conveyor feeding in a cosmetics production line. The system integrates (i) perception modules for object recognition, bottle pose estimation, grasp affordance estimation, and socket tracking, (ii) classical motion planning for robust pick trajectories, and (iii) a machine-learned controller for dynamically adapting the “place” motion to a potentially moving target socket.

In addition, the system targets rapid task reconfiguration through a generate-and-refine workflow that uses LLM-based code generation [67], [68], [69], [70] combined with simulation-based feedback in Isaac Sim [71]. This supports fast adaptation to changing product runs and operating constraints without requiring extensive manual reprogramming.

c) Experimental Setup / Implementation: A practical deployment scenario is drawn from a cosmetics production facility, where robots already perform filling, capping, brush insertion, and packaging tasks. The targeted automation step is currently performed manually: picking unfilled bottles from piles or delivery boxes and inserting them into sockets in carrier blocks moving along a conveyor belt. This task is constrained by limited space (no room for extensive pre-sorting hardware) and by the need for precise synchronization between real-time bottle pose estimation and socket motion to achieve reliable insertion at production throughput. Fig. 16 illustrates the station layout where a robot could be deployed.

The conveyor feeding system is implemented using a UR5e robot arm from Universal Robotics. A separate computer hosts machine vision and robot motion planning components, communicating with the robot via ROS2 APIs [72]. Motion planning and pick trajectory execution use services from MoveIt2 [73]. Grasp affordance estimation computes a 6DoF gripper pose and 3D approach direction using a multi-stage pipeline that combines off-the-shelf neural models with point cloud segmentation and shape fitting, selecting an accessible bottle for picking.

After grasping, a wrist-mounted camera provides refined relative pose estimation of the bottle to set the start state for motion planning toward the insertion area. For the placement phase, joint action planning is performed by a custom machine-learned model trained to adapt the robot motion based on real-time robot state and target socket state. Socket tracking uses a fine-tuned machine vision model based on YOLOv9 [74], [75]. Inputs to the placement controller consist of joint angles and velocities (from ROS2) and the current 2D position and velocity of the target socket; outputs are joint actuation commands (desired joint velocities and angles for the next time step) sent to the robot controller via a customized ROS2 action controller.

d) Results and Insights: The integrated system architecture demonstrates how combining classical robotics with learning-based components enables robust automation under realistic industrial constraints. MoveIt2-based motion planning provides reliable pick behavior, while the learned placement controller supports dynamic adaptation to moving sockets using real-time state inputs. The use of fine-tuned perception models (YOLOv9-based socket tracking) improves robustness in the presence of variable object and target configurations. At the workflow level, LLM-assisted task reconfiguration paired with simulation feedback supports faster iteration and reduces engineering overhead for frequent product changes.

This case study further illustrates a practical spectrum of AI integration: from off-the-shelf components (MoveIt2 motion planning, externally hosted LLM assistants), to fine-tuned pretrained models (YOLO), to custom neural models trained specifically for dynamic placement control. Together, these choices address key constraints of small-to-medium manufacturers, including limited space, limited engineering resources, and frequent task switching.

e) Implications and Transferability: This use case highlights a transferable integration pattern for industrial pick-and-place automation: combine modular perception, reliable classical planning for nominal motion generation, and learning-based controllers for high-variability sub-tasks where adaptation is essential. The generate-and-refine workflow using LLM code generation and simulation feedback offers an extensible strategy for rapid task reconfiguration beyond cosmetics manufacturing, particularly in settings with frequent product changes and limited commissioning time.

More broadly, the approach demonstrates how layered AI methods can improve automation performance while managing deployment risk: by constraining learned components to the most uncertainty-sensitive parts of the task (e.g., dynamic placement) and retaining proven planning and control frameworks for the remainder of the system.

D. Machine Learning Operations for Semi-Supervised Data Annotation

a) Problem Description: While machine learning models offer significant potential for industrial automation, their practical deployment and management extend far beyond initial training. In dynamic manufacturing environments, models face challenges such as data drift, where real-world data changes over time, causing performance to degrade. Manually managing the entire ML lifecycle, from data collection and annotation to retraining and redeployment, is inefficient, prone to error, and not scalable. One of the challenges addressed within the project is the operationalization of ML models in a structured manner, with one application being a semi-supervised data annotation pipeline. Without a dedicated MLOps framework, it would be difficult to consequently analyze the model’s incremental improvements in the semi-supervised loop, systematically compare parallel runs to select the most effective configuration, and continuously monitor model-related metrics to make informed decisions within the pipeline.



Fig. 16: Overhead view of a production line station where bottles are placed onto a conveyor

b) Approach: To address the challenges of manual annotation and model degradation, we propose an iterative, MLOps-driven pipeline for semi-supervised data annotation. The process begins by presenting a small, representative sample of manually annotated data to the system. Experimental results demonstrate the high data efficiency of this method, showing it functions effectively with an initial set of as few as 10 samples. Utilizing this seed dataset, an initial training phase involving multiple set of hyperparameters is conducted, after which the best-performing configuration is selected to serve as the baseline model. Potential extension of the method could involve training multiple architectures at once and selecting the baseline model among them.

Once established, this baseline model is deployed to generate pseudo-labels for the larger pool of unlabeled data. This initiates the core semi-supervised learning loop, where the newly generated pseudo-labels are evaluated, which relies on a composite confidence score, which is assigned based on both the model's inherent prediction confidence and the embedding similarity of the detected objects.

The operationalization of this iterative loop relies heavily on the MLOps practices. Pseudo-labels that exceed a high-confidence threshold are automatically converted into true ground-truth annotations and appended to the training set. A dedicated data versioning system manages this integration, capturing a snapshots of the dataset as it evolves to guarantee full reproducibility across iterations. This newly versioned dataset subsequently triggers an automated training pipeline, which retrains the baseline model without the need to manually annotate or review the labels.

The automatically retrained model is then deployed to infer a new set of pseudo-labels for the remaining unlabeled data, it-

eratively refining the dataset's quality. This cyclical process of generation, confidence evaluation, automated data versioning, and model retraining continues until the termination criterion is met. For the conducted experiments, when the change in the number of high-confidence labels produced between successive iterations falls below a specified threshold, the process stops, indicating pipeline convergence.

IV. CONCLUSIONS AND IDENTIFICATION OF FUTURE STREAMS FOR RESEARCH AND DEVELOPMENT

The described applications in practice—from material handling to intralogistics and production management (Table III)—show the interconnectedness of engineering-oriented solutions (e.g., robotic handling, health monitoring of automated transport systems) and management-oriented methods (e.g., fleet management, variability reduction, bottleneck identification). These examples, spanning industries such as cosmetics and semiconductors, highlight how the joint application of engineering and management perspectives contributes to the operational efficiency and resilience of modern production systems.

The applied approaches rely on and make use of the increasing availability of industrial data. Both heuristic methods, such as rapid modeling, and data-intensive techniques, such as computer vision, supervised learning, and reinforcement learning, are complemented by human reasoning and decision-making support (e.g., SHAP-based explainability). Together, these approaches demonstrate that hybrid solutions—combining data-driven methods with domain knowledge and interpretability—yield promising results in practice.

As summarized in Table III, several insights can be derived. First, machine learning does not replace established production

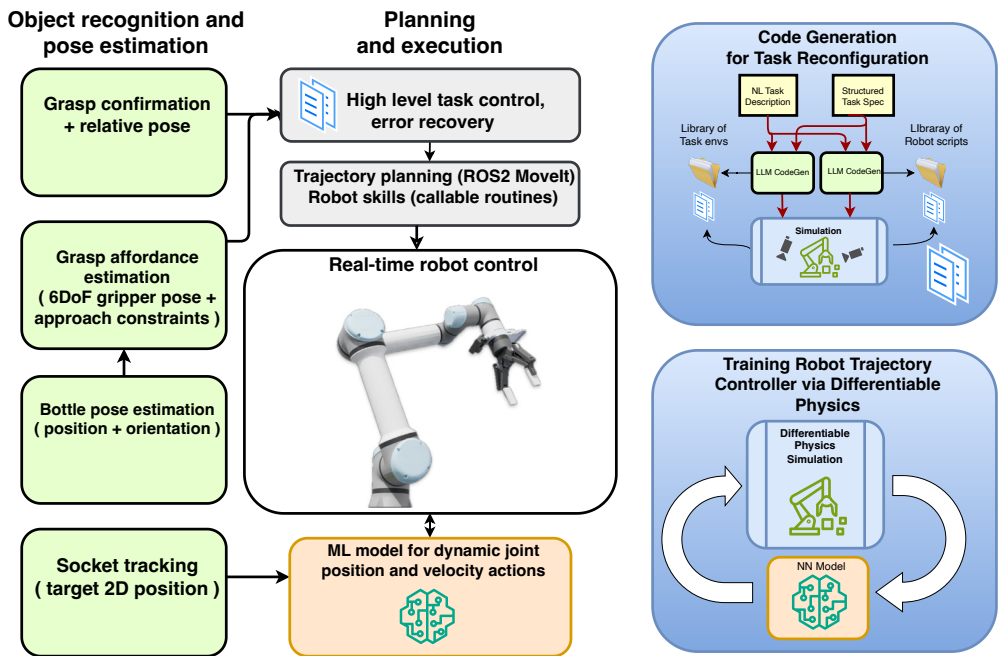


Fig. 17: System Overview. Green boxes (on the left) are components that supply real-time data to the robot control system. Blue boxes on the right represent training-time (prior to deployment) systems that produce scripts and machine-learned models for deployment into the runtime system (central column).

TABLE III
OVERVIEW OF PRESENTED APPLICATION AREAS, OPERATIONS, CHALLENGES, AND APPROACHES IN MANUFACTURING.

Application	Operation	Industry	Challenge	Approach
Material handling Picking and placing	Assembly and commissioning of components on conveyor belt	Cosmetics	Accuracy, safety in human-robot collaboration, and adaptation to frequent product reconfigurations	Computer vision and reinforcement learning for adaptive control systems
Intralogistics Fleet management	Transportation task assignment and route planning of AMRs	Semiconductors	Coordinating AMR fleets with >1,000 possible locations in real-time	Predicting travel times using supervised learning on log-files
Health monitoring	Automated transportation carrier	Semiconductors	Recognizing imminent malfunctions of the automated transportation system	Using low-cost sensor platform
Production Variability reduction	Process variability at work-station	Semiconductors	Identifying impact of process variability on flow time and utilization	Rapid modeling technology based on networks of queuing models
Bottleneck identification	WIP levels in front of work-station	Semiconductors	Short-term prediction of WIP levels and identifying influencing process variables to mitigate bottlenecks	Prediction of WIP levels using XGBoost and visualization of local feature importances with SHAP values

and process management methodologies but amplifies their impact when properly integrated. Further, the chosen methods must be tailored to the specific challenges of the application domain: reinforcement learning for adaptive robotic control in cosmetics, supervised learning for intralogistics fleet optimization in semiconductors manufacturing, or rapid modeling for analyzing variability in production flows. Additionally, across domains, the combination of digital methods and managerial practices shows the potential to create more adaptive, efficient, and sustainable production systems capable of coping with rising complexity and variability.

Overall, the experiences gathered in the project AIMS5.0 illustrate how interdisciplinary collaboration can turn advanced methods into operational improvements, offering a pathway toward more intelligent, connected, and robust manufacturing systems.

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