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Towards Smart Autonomy – A Concept for a Smart Robotic Assembly Cell

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Abstract: Production companies in Austria, especially small- and medium sized Enterprises (SMEs) undergo significant changes. While customers increasingly demand customization of products, companies increasingly move towards digitalization and automation of processes to manage the increasing complexity within the processes. In this paper, these challenges were addressed by developing a concept for a smart robotic assembly cell, that is capable of managing a large variety of different products and reducing human-induced errors during the manufacturing process. The concept was validated with a real-life robotic assembly-cell at the University of Applied Sciences in Wiener Neustadt and a series of tests show promising results in managing complex manufacturing processes by utilizing tools of Artificial Intelligence (AI) and interconnected productions systems (IIoT).

Keywords: Artificial Intelligence, Automation, Process Optimization, Interconnected Production Systems

1. INTRODUCTION

European industry is currently undergoing significant changes. Progresses in automation and digitization transform European industry at a rapid pace (*A vision for the European industry until 2030 – Final report of the Industry 2030 high level industrial roundtable*, 2019). Companies need to adapt to remain competitive in the global market. Increased personalization in products at the price of mass production is becoming the benchmark for competitive companies. Customers demand an increasing number of product variance while keeping cost and delivery time down (Mayrhofer et al., 2023). The trend to produce a high mix of products in low volume (HMLV), however, poses additional challenges, especially for small and medium sized enterprises (SME). Effective capacity planning, the alignment between demand and available capacity, efficient order release, and the preventive detection of failures – only to name a few – become increasingly important as the level of flexibility within a production company rises (Hörbe & Erol, 2024). These planning tasks, including the assembly process, are still performed by hand in most SMEs. The automation of tasks, especially the usage of robots in a human-robot collaboration, can offer some significant benefits, such as health protection of human workers, increased agility and improved competitiveness (Karaulova et al., 2019). Automation requires a degree of predictability and is usually used in production lines with low variance and high production volume (Burggräf et al., 2019). The more flexible a production line becomes, the more challenging the assembly task is, as the robot program must be adjusted to new product variants without sacrificing production output(Simeth et al., 2022). Artificial Intelligence (AI) has proven to be a valuable addition to SMEs in order to deal with the challenges of HMLV-production, especially in the fields of quality control

(Saurer et al., 2025; Shaloo et al., 2023; Shaloo et al., 2024), scheduling (Liu et al., 2022; Zhao et al., 2021) and maintenance (Ansari et al., 2019; Princz et al., 2024). Artificial Intelligence has the potential to automate tasks that were initially too difficult to be automated (Soori et al., 2023), but there is still demand for innovation and improvement. According to Johansen et al. (2021) it is needed to explore automation-assisted assembly solutions in order to achieve improved productivity and to increase customer value. According to Dwivedi et al. (2021) there is also an opportunity to improve the reliance of automation with the usage of AI. This paper aims to explore the application of artificial intelligence in automated HMLV production to overcome challenges that could not be overcome by means of automation alone. To achieve this goal, an autonomous robotic assembly cell is created, which produces a robotic gripper in a large number of variants. State-of-the-art Artificial Intelligence algorithms are implemented to mitigate challenges which are known in HMLV productions (Hörbe & Erol, 2024), and formulate recommendations for production companies. Hence, this paper contributes to the State-of-the-art by evaluating AI algorithms on a real-world automated production cell and can serve as a baseline for implementations in HMLV production lines. The paper is structured as follows. The state-of-the-art is identified and discussed, showing similar work that has been done in the field. In the chapter Methodology, the approach as well as the architecture of the robot cell is explained. Based on the conducted methodology, the results are evaluated and conclusions as well as recommendations are drawn.

2. STATE OF THE ART

The HMLV manufacturing industry has grown significantly, leading to increased research efforts aimed at enhancing manufacturing flexibility. (Gan et al., 2023) reviewed 152 publications from 2000 to 2022. Their study indicates that production planning is the central focus of research, with particular attention given to the semiconductor and electronics industries. Furthermore, Industry 4.0 technologies play an important role in supporting decision support systems for reactive production planning. The study also shows that robotics and automation systems have recently been widely applied in assembly systems.

The main challenge in HMLV production is managing a high product mix while maintaining operational efficiency. In such environments, individual orders often require unique processing routes and specific setups, increasing complexity in scheduling, machine utilization, and workforce planning. These difficulties become even more pronounced as companies aim to ensure short lead times and consistent quality across a wide range of products (Bohnen et al., 2011; Gan et al., 2023) .

Gan et al. (2023) represented that recent research has focused strongly on robot programming for flexible manufacturing and the application of Industry 4.0 concepts. In particular, real-time data collection, decision-making systems, forecasting methods, and reinforcement learning have attracted significant attention from researchers. HMLV manufacturing involves a wide variety of raw materials, processing times, procedures, and production flows, which necessitates flexible assembly lines capable of handling product variety and absorbing volume fluctuations (Gan et al., 2023). In this context, (Asadi et al., 2019) examined the use of mixed-model assembly lines (MMALs) and mixed-product assembly lines (MPALs) in a case study. Their main challenge in

MPALs was the low level of product modularity. Establishing a common assembly sequence and similar modules across product families would enable the transition to a more flexible system with higher mix capability.

Johansen et al. (2021) reviewed the role of automation in HMLV production. Becker und Scholl (2006) distinguish three types of assembly lines: single-model assembly lines, mixed-model assembly lines, and multi-model assembly lines. In mixed-model assembly lines, different product variants can be assembled simultaneously on the same line (Hu et al., 2011). Mixed-model assembly (MMA) lines can therefore be considered a typical example of high-mix, low-volume production, where products are manufactured in small batches.

Industry 4.0 technologies significantly enhance flexibility and responsiveness in HMLV production environments. By integrating cyber-physical systems, additive manufacturing, traceability solutions, and data-driven decision support systems, manufacturers can better manage high product variety, dynamic scheduling requirements, and individualized production processes. These technologies form the foundation for intelligent, adaptive, and efficient HMLV manufacturing systems (Gan et al., 2023).

Within the context of flexible production, robotics and automation are increasingly evolving to meet the specific requirements of HMLV manufacturing. Recent developments emphasize collaborative robotics, advanced automation technologies, and the integration of robotic systems within Industry 4.0 frameworks. Research has addressed multi-robot coordination in flexible batch manufacturing systems, proposing algorithms and simulation-based approaches to overcome bottlenecks and improve system performance (Ruppert et al., 2018). At the same time, the high variation of products in HMLV environments requires frequent robot reprogramming, prompting the development of new methods and tools aimed at reducing setup time and programming effort. These advancements contribute to making robotic systems more adaptable, efficient, and suitable for high-variability production settings (Gan et al., 2023).

The state of the art reveals a transition from theoretical planning models toward integrated, cyber-enabled systems where robotics and digital technologies play a central role in enabling HMLV flexibility. However, gaps persist in implementing holistic solutions based on complex real-world HMLV conditions (Powell, 2018) that seamlessly combine human expertise, robotic adaptability (Solyman et al., 2020), and real-time decision support (Ojstersek & Buchmeister, 2020) across the entire production value chain.

3. METHODOLOGY

Specific challenges, faced by SMEs in Austria were identified using a series of qualitative interviews in Eastern Austria (Hörbe & Erol, 2024). A total of 12 interviews were conducted with companies following a HMLV approach in production. Among the challenges, the most important were that companies do not have sufficient control of workorders, unbalanced work systems and insufficient failure detection and prevention during the production process. A structured literature review was conducted to research state-of-the-art for identified challenges. While ongoing research was identified in failure prevention and detection as well as balancing work systems and production planning, a practical approach towards monitoring and controlling work orders during production is still to be researched. Therefore, there is a demand for improvements to increase transparency during an ongoing production process. The results of the interviews and the literature research were published priorly (Hörbe & Erol, 2024) and are publicly accessible on the project website (Fachhochschule Wiener Neustadt, 2025). Based on the results of the qualitative study, a demonstrator was set up at the Innovation Lab of the University of Applied Sciences Wiener Neustadt to demonstrate possible solutions for the identified challenges of highly automated production processes.

3.1. System Overview

To address the automation challenges of HMLV production scenarios, an autonomous robotic assembly cell was developed and experimentally evaluated (Figure 1). The cell is structured around two core functions of commissioning and assembly which are often treated separately in variant-rich manufacturing. During commissioning, components are automatically identified, localized, aligned, and stored in predefined buffer locations. Assembly is initiated, once all components required for a product variant are available.

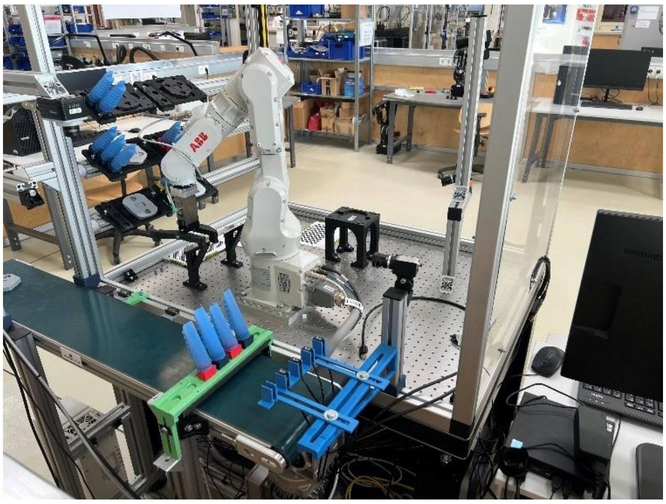

Figure 1: Robotic assembly cell

A robotic soft gripper serves as the demonstrator product. It consists of a base plate available in two different geometries and a configurable finger set with either two or three fingers, enabling the evaluation of multiple product variants (see Figure 2 and Figure 3). By combining different finger types, colors, shapes and quantities a total of 144 different variants can be provided (Böck, 2024).

Figure 2: Parts overview

Figure 3: Robotic gripper

3.2. Cell Layout

The robotic cell combines a conveyor-based infeed for base plates with a holder-based infeed for fingers. Both component types are stored in dedicated storage locations within the cell. Cameras are used for part classification and pose estimation, while photoelectric sensors (light barriers) enable event-based triggering and component presence detection. To increase robustness during the put-away process, an alignment station is integrated to compensate for pose estimation inaccuracies prior to final storage. Assembly is performed at a universal assembly station designed to support variant-rich operations.

The overall control strategy follows an event-driven architecture. Perception and measurement routines are triggered by discrete sensor events (light barriers) rather than continuous sensing. This approach establishes defined and repeatable states within the material flow, thereby improving the reliability of the overall process. A labeled overview of the cell layout is provided in Figure 4.

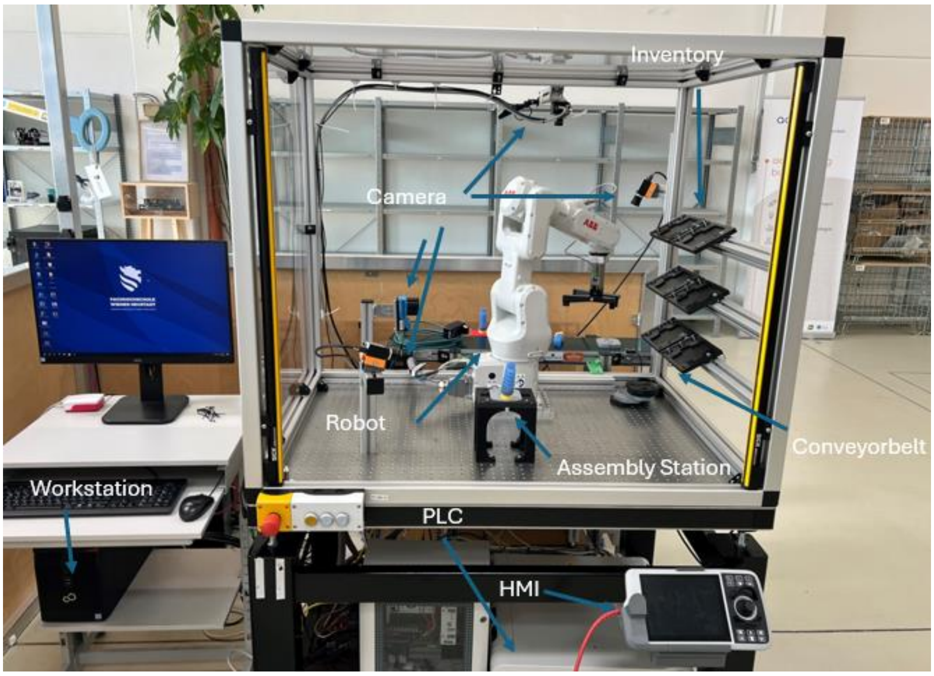

Figure 4: Labeled cell overview

3.3. Commissioning of Base Plates

Base plates are manually placed onto the conveyor and transported into the robotic cell. When a base plate passes the first light barrier, a perception routine is triggered and a YOLOv8-based model (Jocher et al., 2023) classifies the base plate type. The identified class determines the appropriate handling routine and target storage location.

To enable the communication between a YOLO model, which runs on a workstation and the robot, which is controlled by an ABB robot controller, a TCP socket (Python Software Foundation, 2026) was used where the workstation acts as the server and the robot controller the client. Once the connection is successfully established, the identified class, provided by the YOLO model, enables the robot to execute variant-specific actions based on the results of the YOLO model.

The YOLO model achieves an inference time of about 5ms, which would theoretically send 200 results per second to the robot. However, preliminary tests showed that the precision of the YOLO model decreases when the object to be identified is located at the edge of the field of view, particularly while the object is in motion, as is the case when entering the camera view on the conveyor belt. To overcome this challenge, once the light barrier is triggered, the conveyor belt is stopped, ensuring stable conditions for the object detection. The YOLO model is then triggered exactly once. If a valid class is passed to the robot, the YOLO model is not triggered again, and the robot controller takes over the next actions.

After classification, the base plate continues along the conveyor until it reaches the second light barrier, which initiates pose estimation. At this point, image acquisition is triggered by the robot, and the vision system computes the pose of the base plate (position and orientation). The robot uses the estimated pose to pick the part and transport it toward the storage area.

Practical trials revealed that pose estimation can vary between runs, which reduces placement reliability if parts are deposited directly into storage. To ensure robust and repeatable put-away, the base plate is first placed into an alignment station where it is mechanically aligned to a defined position. Only after this alignment step is the part deposited into its final storage location. This strategy decouples pose uncertainty from storage positioning and standardizes part position, improving repeatability and downstream process stability.

3.4. Commissioning of Fingers

Fingers are supplied via a dedicated holder system. Before any pick operation is executed, the presence of a finger is verified using light barriers to ensure that only available components are handled. The commissioning process follows a two-stage pipeline. First, the robot picks a finger from the holder and presents it to the vision system, where a YOLOv11-based model (Jocher & Qiu, 2024) classifies the finger type. After successful identification, the robot transports the finger to its assigned storage location and deposits it. This sequence ensures that fingers are stored consistently and correctly based on confirmed type information. The reason for deploying different YOLO models is the swift progress in YOLO models during the duration of this study, which aimed to integrate state of the art models. Again, the deployment of the YOLO model is similar to the model used for base plate commissioning, meaning the YOLO model communicates with the robot controller via TCP socket and is triggered only once to avoid overloading the robot controller.

3.5. Assembly Trigger and Experimental Procedure

Conceptually, the cell is designed to initiate assembly once the internal storage contains all components required for a customer order, meaning that assembly starts only when an order is complete from an inventory perspective (base plate plus required fingers). At the time of validation, however, the end-to-end automation of order capture and full coupling to the order logic were not yet finalized. Therefore, the assembly process was manually and repeatedly triggered during experimentation to measure process stability and cycle times under controlled conditions.

The experiments included gripper variants with two fingers as well as variants with three fingers in order to systematically assess the impact of increased variant complexity, specifically the additional components and assembly steps, on performance and robustness.

4. RESULTS

The described YOLO models were expanded and deployed within a Bachelor’s thesis (Tenzin, 2024) and a Master’s thesis (Fritsch, 2025). The YOLOv8 model was trained for 100 epochs, using a total of 1,360 pictures while the YOLOv11 model was trained for 50 epochs using 675 pictures.

Both models were evaluated after training using precision, recall and F1-score as well as the confusion matrix (Figure 5, Figure 6). The precision evaluates the rate of the correct instances of all identified instances of each class. The recall measures, how many actual instances of a class were identified by the model, while the F1 score is the harmonic-mean between precision and recall. The confusion matrix illustrates the relation between predicted and actual class. (Ultralytics Inc., 2026)

The YOLOv8 model achieved a precision of 100% for all classes but one, which still achieved 96.67% precision. The recall was also 100% for all classes but one with a precision of 96.77% recall. As a further result, the classes with a precision and recall of 100% came with the F1-score of 100% (Tenzin, 2024). The remaining two classes with lower precision and recall had a F1 score of 98.36% and 98.31% respectively. The YOLOv11 model achieved an average precision, recall and F1-score of 99.95%, 100% and 99.979% respectively (Fritsch, 2025). While the YOLOv8 model showed a stable performance during live deployment, the performance of the YOLOv11 model dropped notably, to a precision of 70%, a recall of 93% and a F1-score of 80%. This was due to unreliable predictions as the object did not enter the camera's field of view completely. After configuring the YOLO model to be triggered only once the robot had fully positioned the finger within the camera's field of view, the system performance recovered, achieving 100% across all three evaluation metrics.

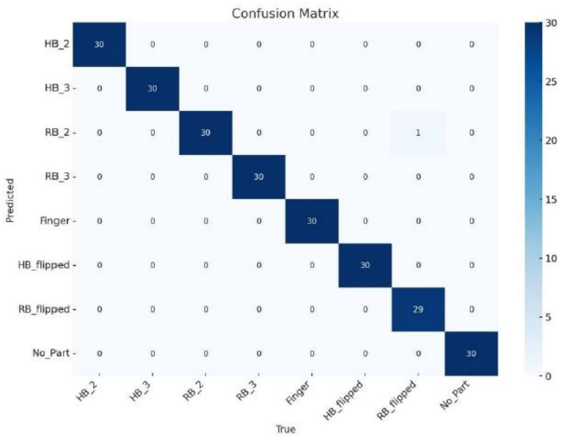

Figure 5: Confusion matrix YOLOv8 model for base detection (Tenzin, 2024)

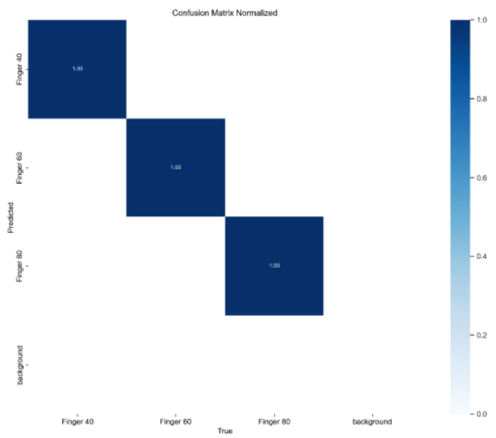

Figure 6: Confusion matrix YOLOv11 model for finger detection (Fritsch, 2025)

To evaluate the developed robotic cell, assembly runs were conducted under controlled conditions. Since fully automated order triggering had not yet been integrated at the test stage, the assembly sequence was executed repeatedly in a sequential manner to evaluate process stability, success rate, and cycle time. The evaluation was conducted over both two-finger and three-finger variants.

In total, 120 assembly trials were performed, comprising 320 individual assembly steps. Across these trials, 95% resulted in successful assemblies, indicating a high baseline process capability in variant-rich assembly using vision-based recognition and robotic handling.

As expected, average cycle times differed between the two variant classes. For two-finger variants, the average assembly time was 54.808 seconds and was reduced to 53.173 after improvements. For three-finger variants, the average assembly time was 75.585 seconds and was reduced to 71.557 after improvements. These results confirm that three-finger variants exhibit significantly higher cycle times due to additional handling and assembly steps. The measurements show that targeted improvements reduced average cycle time for both variant classes with the most notable reduction observed for the three-finger variants (Böck, 2024).

5. CONCLUSION

In this study, the potential impact of Artificial Intelligence on highly automated HMLV productions was evaluated. Previous research identified several promising use cases (Hörbe & Erol, 2024), from which a selected subset was further developed and experimentally investigated in this work. By implementing the proposed concept within a real-world robotic assembly cell, the approach could be validated using operational production data rather than relying solely on performance metrics obtained during AI model training.

YOLO models were utilized to identify objects during the production process and communicate with the ABB robot controller via TCP socket communication. The high success rate during demonstration shows the practical applicability of Artificial Intelligence in addressing the key challenges of highly automated HMLV production. The experimental validation demonstrates a high success rate across repeated assembly cycles, while also revealing a clear dependency of cycle time on variant complexity. These findings support the technical feasibility of a largely autonomous robotic assembly process capable of handling multiple variants.

Nevertheless, several limitations must be acknowledged. Only a limited number of the identified use cases were implemented, which leaves room for future research to close the identified gaps. Although the developed robotic gripper allows for the production of 144 distinct variants, real-world HMLV environments may involve thousands of variants or even fully individualized products.

This substantially increases system complexity, particularly regarding the availability and scalability of training data for machine vision models such as YOLO. Future studies should therefore focus on strategies for handling extreme product variability in automated HMLV productions.

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