DIGITAL TWIN DRIVEN ASSEMBLY LINE RE-BALANCING AND DECISION SUPPORT

Giovanni Lugaresi[1], Kovacs Laszlo[2], and Kornel Tamas[3]

[1]Department of Mechanical Engineering, KU Leuven, Leuven, Belgium, e-mail: giovanni.lugaresi@kuleuven.be
[2]Department of Automation and Applied Informatics, Budapest University of Technology and Economics, Budapest, Hungary, e-mail: kovacs.laszlo@vik.bme.hu
[3]Department of Machine and Industrial Product Design, Budapest University of Technology and Economics, Budapest, Hungary, e-mail: tamas.kornel@gt3.bme.hu

KEYWORDS

Digital twins; assembly lines; production control; Industry 5.0; work assignment; re-balancing.

ABSTRACT

Recent investments in industrial digitization together with the concrete need for short-term planning capabilities mean digital twins can effectively aid enterprises in the management of their production systems and value chains. This paper introduces a conceptual framework for assembly line re-balancing in the context of Industry 5.0, focusing on manual assembly processes. The framework aims to leverage a digital twin for obtaining a synchronized representation of the current task allocations in the assembly line, and uses data-driven scenario generation methods for investigating alternative balancing solutions that are proposed to operators in real time. A proof-of-concept platform is implemented in a laboratory environment, utilizing an assembly line with industrial components. Preliminary results demonstrate the compatibility of the proposed components within the digital twin framework. The potential applicability to various manual assembly scenarios is discussed, along with considerations for incorporating additional constraints in the evaluation process.

INTRODUCTION

Manufacturing companies are recognized for delivering high-quality products tailored to customer specifications. Achieving stringent standards while managing product and process variability is challenging, also considering that companies face with elevated costs of labor. This is particularly crucial in production sectors with substantial labor involvement and operating under takt time, such as assembly lines. Meanwhile, resilience, sustainability, and human-centric production are the cornerstones of the new Industry 5.0 paradigm (Ivanov, 2023), which focuses to improve production processes involving interactions with human workers.

Assembly is the pivotal production process for generating products with numerous variations, relying on a relatively small set of standardized modules. Assembly processes heavily rely on specialized human labor, with nearly a third of employees in the European metal and electronic industry engaged in assembly work (Monika, 2021). As product intricacy continues to grow, accompanied by a shrinking pool of human resources and escalating labor costs, the efficient utilization of human labor in assembly processes emerges as a critical factor for European industry and its global competitiveness. Given the high cost of labor, a typical goal is to minimize the under-utilization of the human workforce, which is challenging given the diversity of assembly tasks and their resulting processing time variability from one order to another. Line balancing involves grouping assembly processes, assigning them to workstations and workers, defining workstation borders, and establishing the takt time. It is among the planning steps with the most significant impact on worker efficiency (Becker and Scholl, 2006; Battini et al., 2020).

Despite advances brought by recent approaches exploiting hardware reconfigurations and flexible layouts (Hottenrott and Grunow, 2019), modern assembly systems face new challenges. First, the push toward high customization means a high variability of product variants. Several companies aim for one-piece-flow capable systems. However, the production control algorithms are typically not designed to be dynamically changed, potentially even after each work-piece. Also, the ever-increasing diversity in the workforce (ageing, re-training, and re-skilling are some of the main factors) results in high variability of worker's productivity levels, which is visible even within a single day (Lassila et al., 2004; Silva et al., 2013). The result is that an optimal solution with a certain workers' setup may result sub-optimal with another. Smart system and production assets reconfigurations are needed to face this challenge, while monitoring and supervision systems alone are not enough. There is the need to provide a proactive digital-to-physical interaction. In order to correctly evaluate alternative production scenarios, an up-to-date model of the real system must be readily available whenever needed. Also, a smart decision support system must be able to quickly learn the system's features and to generate alternative scenarios autonomously, and the insights learned from the digital world should be readily applicable in the physical system. This paper presents a research project aiming to overcome the aforementioned limitations with the proposal of a digital twin (DT) framework for manual assembly line re-balancing and online reconfiguration.

PROBLEM STATEMENT

As manufacturers face an aging workforce and seek to implement more flexible work shift models in assembly, recent approaches propose fixed shift schemes but in more adaptable settings, where there is no fixed start and end of shift and workers are allowed to engage at various times, receiving real-time workload assignments (Boysen et al., 2022). However, these approaches remain at a conceptual level: to be effectively applied they necessitate the capability to dynamic rebalance and to re-allocate tasks between available workers, while considering factors such as worker qualifications, learning curves, and the current system configuration to search for an optimal one (Cimen et al., 2022). The goal is to ensure a smooth adaptation process without overburdening the existing workforce, allowing for flexible cycle time adjustments based on the current system state.

A correct and optimal (re)-balancing and task allocation solution can only be obtained and verified if a valid model of the system is available and synchronized with the system state. These are the characteristics of simulation-based DTs (Tao et al., 2018). Indeed, by simulating production runs, planners can forecast the impact of production modifications beforehand (Monostori et al., 2016). Virtualization also aids in tracking parts and products in real time throughout the production process (Uhlemann et al., 2017). Recent approaches demonstrated the capabilities of generating accurate digital models starting from available data in business and production processes (Van Der Aalst and van der Aalst, 2016). Process mining emerges as a valuable tool in the realm of digital twinning, proving its efficacy in several tasks such as model generation, trace profiling, and performance evaluation. The capability for an automated generation of a simulation model paves the way to achieving a DT that is able to provide in real-time actionable insights to a manufacturing system (Lugaresi and Matta, 2021; Pourbafrani and van der Aalst, 2023). Complex manufacturing processes such as assembly are characterized by multiple interacting objects, which necessitates the application of novel approaches based on object-centric process mining (Lugaresi and Matta, 2023). However, the application of such model generation techniques to assembly system remains limited to synthetic data (Lugaresi and Matta, 2023). Besides, to the best of our knowledge there have been no implementations of complete DT architectures (i.e. from shop floor data to actions) in real environments for production planning and control applications. The current methods often involve the presence of managers/operators to define the search space and the desired performance levels. This slows down the decision-making process, together with the risk of obtaining sub-optimal solutions. Currently, the maturity/automation levels of a DT have been defined (Uhlenkamp et al., 2022) but not implemented, nor benchmarked with existing case studies. Current scenario generation approaches are limited to optimization approaches (Bounitsis et al., 2022) while there are no clear contributions that integrate with simulation-based methods and keep into account the real-time constraints for short-term decision making. Hence, there is the need to provide insights from test cases with real industrial equipment.

The research project presented in this paper aims to design and implement within a proof-of-concept platform a flexible DT of supervised assembly processes. The project takes as reference a setup available at the Industry 4.0 laboratory of Budapest University of Technology and Economics. The setup is a replica of a real assembly process in the automotive sector. Within this setting, the project aims at (1) testing a state of the art model generation technique with a real system dataset (i.e. industrial logic controllers and Manufacturing Execution System) and gather insights and data requirements from the behavior of model generation techniques facing unpredictable changes in a flexible assembly system; (2) designing and testing a method for feature's extraction and automated scenario generation, to proactively investigate if better solutions can be achieved on the line in real time; (3) designing and testing a method for DT-driven decision support for flexible assembly systems. The goal is to continuously compare the proposed solutions from the DT and provide actionable insights online to reconfigure the production. This paper contributes in (1) outlining the research project with respect to the literature, (2) presenting the main steps of the proposed methodology, and (3) presenting preliminary results obtained in the available setup.

RELATED WORK

In order to select relevant papers and worthy a comparison with this work, the following query has been done on Scopus on 9-Feb-2024: *"digital twin"* AND *"assembly"* AND (*"re-balancing"* OR *"balancing"*). The search results in 13 papers[1]. Among them, 8 papers are considered based on these criteria: (1) the paper regards production systems (2) the DT is used during the production operations, (3) the DT purpose is faithful to the definition (i.e., feedback loop of information). Also, one paper has been added following a

[1] List of papers: http://tinyurl.com/sota-dt-assembly

forward-backward citation analysis. Table 1 collects the selected contributions for comparison.

Selected Works

Zhang et al. (2022) introduced a reconfiguration framework for assembly lines with frequent changeovers, exploiting DTs based on an open architecture for both equipment and the assembly line, facilitating swift physical reconfiguration. The proposed technique is based on the idea of using DT-based predictive simulation for testing possible changeover schemes to reduce changeover times in real cases. An optimal reconfiguration algorithm is presented which employs analytical target cascading to address the joint optimization of order scheduling, line balancing, and buffer allocation.

Pabolu and Shrivastava (2021) proposed a dynamic solution to the worker assignment assembly problem. The fatigue-inducing factors are detected from the workers and classified, then forwarded to a worker-job rotation search algorithm. The algorithm generates recommendations for the production supervisor and suggests optimal dynamic solutions for worker job rotation or reallocation based on fatigue details.

Pabolu et al. (2022) leveraged DT for predicting the task execution time of an assembly line and integrating the forecasted values in an assembly line work assignment framework. The authors propose a human-in-the-loop decision making cycle, in which task execution times are estimated online and used to update alternative assignments evaluated by an heuristic algorithm. The results are then proposed to a line supervisor for reconfiguration decisions.

Yang et al. (2021) addressed the Assembly Line Worker Assignment and Balancing Problem (ALWABP) in which task processing times are influenced by the skill levels of the workers. The authors introduced positional constraints in the ALWABP and presented two mathematical programming models to allocate workers and tasks that address cases in which either new products are introduced or a worker is temporarily absent or leaves a position. The proposed approach is also integrated with a real-time dashboard.

Zhang et al. (2023) explored an adaptable scheduling technology employed in a manual assembly workshop. An analysis is conducted on the DT environment model designed for scheduling: a hierarchical reinforcement learning algorithm is developed to enhance the dynamic adjustment efficiency of the assembly workshop system.

Ragazzini et al. (2021) presented a preliminary DT to solve a a real-time balancing problem in a learning factory based on triggers coming from machine error states. The application of the DT reportedly improved lead time and utilization performance measures when facing unpredicted disruptions.

Xu et al. (2023) established a DT model for a robotic mixed-model assembly line. A mathematical model is developed to minimize reconfiguration costs and optimal load balancing. Authors employ an adaptive neighborhood search algorithm to solve the reconfiguration problem.

Santos et al. (2023) presented a strategy integrating Deep Reinforcement Learning into a Digital Twin framework to establish a training environment closely resembling real-world conditions and employing Discrete Event Simulation to replicate the dynamic aspects of the production system. The experiments demonstrated the effectiveness of dynamic resource allocation to tasks and workers.

Aslan et al. (2023) introduced an approach that utilizes ultra-wideband data for the discovery of process models in manufacturing activities through process mining techniques. The methodology was implemented on an actual assembly line and used to reveal deviations from the prescribed process steps and to identify bottlenecks.

Contribution

Based on the selected papers, we can conclude that: (1) most papers focus solely on either assembly line balancing or workers assignment separately, while the dynamic joint reconfiguration is not addressed, (2) all the works assume the structure of the system and production steps are fixed, and (3) none of the existing papers proposes a specific method to quickly generate alternative scenarios. In this work, we propose a framework that includes the combined assembly line balancing and worker assignment, in which the assembly steps are not preliminary known or may change dynamically during the production. Also, the processing times may be subject to variations (e.g., due to worker's fatigue). The dynamically changing conditions result in the need for model generation capabilities to grasp the dynamics of the system and achieve a higher physical-to-digital fidelity and synchronization.

PROPOSED METHODOLOGY

This research project proposes a methodology for enabling and enhancing the DT-based decision support system on a flexible assembly line. It takes as reference a multi-stage assembly line supervised by a camera for parts recognition. Namely, the operators are guided in picking components from the components kits and a camera-based supervisory system controls the correct assembly sequence and tracks the assembly steps in a time-series database. The system is flexible: both the assembly kits and the operators can be easily moved and interchanged along the line. For instance, the operator of the first station can either assemble all the parts in the kit or a portion of them, leaving the rest for the next operator. The choice depends on the current line balancing policy, the operators' availability and skill-set, together with other contingent factors. As a result, the line can potentially adopt several configurations with a different grouping of assembly steps. Such system can be considered as representative of a large set of other processes that can flexibly change between production resources and operators (Colledani

Table 1: Related works.

Reference	Scope	Method	Input Data	Model Generation	Scenario Generation	Decision Support
Zhang et al. (2022)	Reconfigure System	Simulation	Start-End Timestamps	-	-	-
Pabolu and Shrivastava (2021)	Line Re-Balancing	Heuristic Algorithm	Fatigue	-	-	•
Pabolu et al. (2022)	Worker Assignment	Statistical learning	IoT Sensor Data	-	-	•
Yang et al. (2021)	Worker Assignment & Balancing Problem	Mathematical Programming	Workers' presence & position	-	-	•
Zhang et al. (2023)	Rescheduling	Machine Learning	Multiset	-	-	•
Ragazzini et al. (2021)	Line Re-Balancing	Mathematical Programming	Error States	-	-	•
Xu et al. (2023)	Reconfigure System	Heuristic Algorithm	Multiset	-	-	•
Santos et al. (2023)	Line Re-Balancing	Reinforcement Learning	System State	-	-	-
Aslan et al. (2023)	Process Discovery	Process Mining	Workers Position	-	-	-
This work	Line Re-Balancing & Worker Assignment	Process Mining, Machine Learning	Video Sequences	•	•	•

et al., 2018). The methodology proposed within this research project is summarized in Figure 1.

Data-Driven Model Generation

The information system (i.e., MES, ERP) is responsible to provide tracking data of the assembly operations recorded by the supervision system. First, in order to grasp the system state and the current configuration of the line, the data-driven model generation technique proposed by Lugaresi and Matta (2021) is used to exploit shop floor data for generating a graph-based model of the system. The graph model effectively represents the skeleton of a DT, as it can be converted in a forward-looking model such as discrete-event simulation (Pourbafrani and van der Aalst, 2023). The system parameters are also reflected in the simulation model from the available datasets (e.g., statistical process time distributions). Starting from the as-is model, a continuous performance evaluation process is activated. The simulation model is used to estimate future system performance (e.g., throughput). This is done both in a rolling horizon approach or based on triggers such as a lower expected production output with the current configuration.

Scenario Generation

If the system performance is unsatisfactory as shown by significant deviations from the expected production levels, alternative scenarios are generated for evaluation in the digital realm. Alternatives involve both the shift and re-organization of assembly steps along the stations and the operators order and sequence along the line. The scenarios are generated via a smart exploration of the solution space. For instance, if a certain setup has been observed to be productive in the past (either in the real or in the digital world), the alternative scenarios are generated as close as possible to such configuration. Also, given the availability of a graph-model as DT skeleton, promising solutions can be identified as near to the current situation. For instance, the shift of one task from one operator to the next one can be generated and a reasonable number of solutions can be quickly explored.

Decision Support

The expected performance of each identified scenario is evaluated digitally via simulation experiments. The optimal scenarios are implemented automatically by readily giving operators the indications for a re-setup via the dedicated human-machine interfaces. If changes in the assembly kit are required, respective line operators are informed and operate the change at the next available occasion (e.g., change of shift).

CASE STUDY

Figure 2 shows the available setup at the Industry 4.0 laboratory at the Budapest University of Technology and Economics. The decision-support system proposed in this research project will be installed on the same line, and will provide operators with real-time operational instructions on how to (re)-balance and (re)-allocate the assembly operations.

Test Assembly Line

The purpose of the test assembly line is to be able to test manual assembly processes by continuously monitoring the process and collecting data for its optimization. The line includes three workstations for assembling, beside a place for logistics operations and a quality assurance workplace. The line itself is accessible from both sides. The back side of the line is designed for logistics staff. Here, the logistics operator can create a small buffer storage from the parts arriving from the warehouse by AGV, and then arrange the parts organized in kit trays, one for each of the three

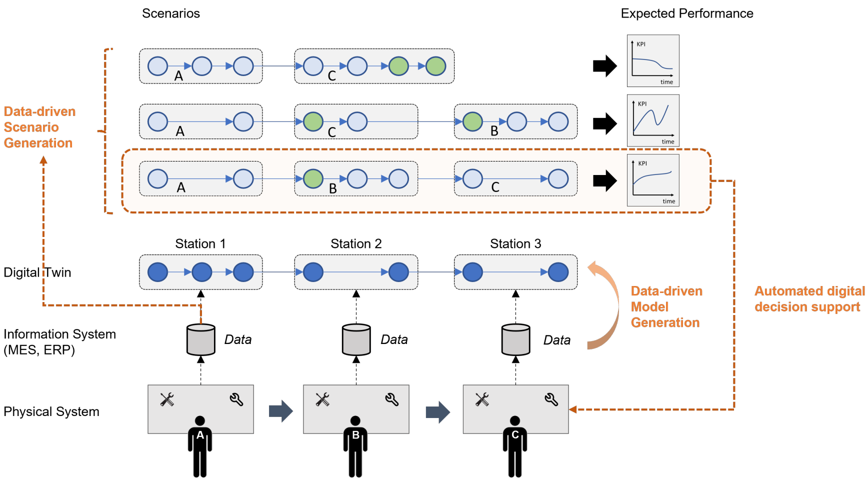

Figure 1: Schematic view of the proposed methodology.

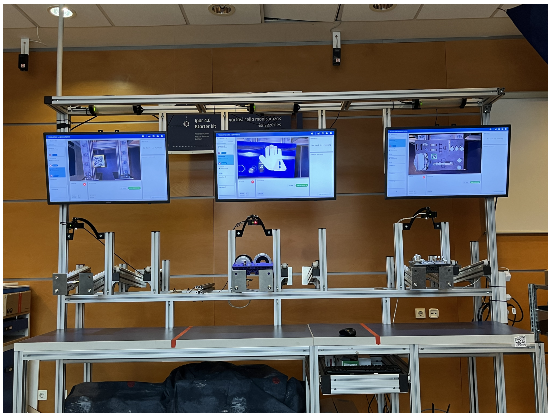

Figure 2: The supervised manual assembly stations (3 operators) in the Industry 4.0 laboratory.

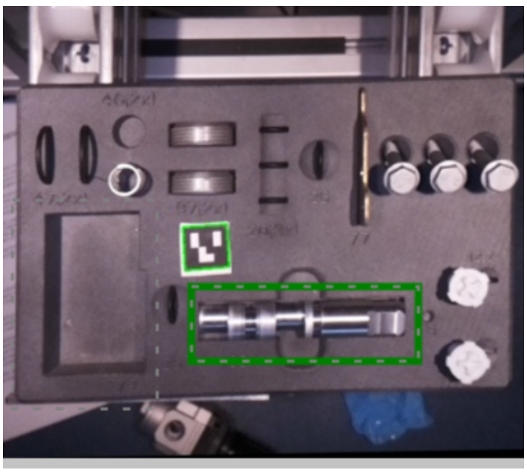

Figure 3: The assembly kit and the identification of components (green box) via the camera according to the assembly sequence.

assembly station. The kit trays are delivered to the operators via a series of inclined rollers. After completing the assembly, the operator returns the empty kit trays on another row of rollers inclined in the opposite direction. During supervised production, the logistics operator receives on-screen instructions on which parts to place on trays 1, 2, and 3, which may change from product to product as a result of optimization.

The front side of the row hosts the workplaces of the the three operators. The kit trays coming from the logistics side stop in a fixed position at the end of the roller row, from where the operator can take out the parts according to the assembly process one by one. A Raspberry PI-based camera units are placed above the kit trays, which monitors the kit trays in real time. Each station is equipped with a monitor which displays the necessary information for the operator and, if necessary, for the shift manager. Additionally, an Andon lamp is placed above each workstation and provides clear visual signals about the current state of the workplace. From the assembly line, the finished workpieces are moved to the quality control workplace, from where the finished products can be placed directly on the AGV.

The assembly process is supported by the Production Line Monitoring (PLM) system. The operators have access to a real-time image of the kit tray on their monitor. When the assembly process starts, the application marks the next component to be installed on the kit tray with a green frame (Figure 3). After the operator has removed the appropriate part from the tray, the image recognition system records the removal of the part as an event with a time stamp in the database. Then, the PLM system marks the next component to be used for the operator. As soon as the operator has completed all the assigned assembly steps, the finished part is placed in the buffer zone between the two workplaces, where the number of waiting parts (depending on the part) is counted with different sensors. The operator can then remove the empty tray from the roller line, thereby sliding the next filled tray into place, and then returns the empty tray to the logistics operator on

Table 2: Extract of data collected from the camera and parts recognition system indicating which component was picked from the assembly kit (assembled parts number 177 and 178).

Time-stamp	Part-Id	Assembly-Name
...	...	...
2/9/24 3:34:17 PM	177	Housing
2/9/24 3:34:18 PM	177	Shaft
2/9/24 3:34:21 PM	177	Screw
2/9/24 3:34:22 PM	177	Spring
2/9/24 3:34:23 PM	177	Plug
2/9/24 3:34:59 PM	178	Housing
2/9/24 3:35:00 PM	178	Shaft
...	...	...

the outgoing roller line.

Collected Data

The data in Table 2 has been extracted in a preliminary experiment, which demonstrates the capability to collect data in real time during the manual assembly operations. The datasets are compatible with model generation techniques and can be used to generate an as-is model of the line. These data demonstrate an ideal usage scenario and do not contain incorrect processes or faulty detection. Each row represents the removal of an item from the tray and therefore, in ideal conditions it corresponds to an assembly step. The columns used in this project are the following: (1) *Time-stamp*: it indicates the date and time of an assembly event; (2) *Part-Id* denotes a specific assembly part. when a product is assembled, a new identifier is created and then used within each step. (3) *Assembly-Name*, which is the specific assembly process which is being performed.

Preliminary Results

A preliminary test has been executed by using the available data set to generate a process model via a process mining-based algorithm (Lugaresi and Matta, 2021), which demonstrated the possibility to generate reliable models describing the real-time system conditions from the available camera setup (Figure 3). Figure 4 shows the obtained process model from the preliminary dataset. The following considerations can be formulated. The video-based acquisition system is sufficient to compose an event log compatible with process mining techniques. The assembly steps are visible in the generated model, as well as the current balancing solution. System performance measures (e.g., activity duration, queuing times) are easily grasped by the generated models and can be readily used to generate alternatives. Process- and resource-based constraints are not visible in the generated representations, and need to be integrated with additional datasets. The generated model is effectively used to evaluate the system performance with the current task assignments. Given the successful model generation on one station, the

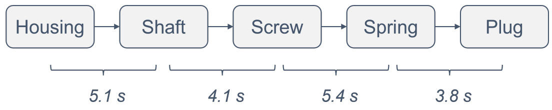

Figure 4: Process model discovered from the preliminary data on station 1 (times are mean values).

next steps within the project involve the generation of a complete model of the whole assembly process and the data-driven generation of line balancing solutions.

FINAL REMARKS

This work proposes a DT driven conceptual framework for assembly line re-balancing in the context of Industry 5.0. Operators can verify the current line configuration based on data driven modeling and performance estimation of alternative line balancing solutions. Preliminary results demonstrated the capability to interface a camera-based real-time supervision system to a model generation procedure.

This research project is subject to several limitations. The literature review can be extended to include works from related fields, such as free-flow production. The proposed framework is incomplete as it lacks of interfaces between components. Also, extensive tests with assembly operators and serial production conditions should be conducted to further validate the proposed setting. The assembly line studied in this work is representative of only a subset of possible production scenarios, with limited constraints that might emerge in other environments. It is well known that line balancing must strictly respect precedence, skill-based (e.g., learning curves), and technical constraints. The inclusion of all these limitations in an automated digital evaluation is not trivial, and will require further work. Future work should also investigate the feasibility of the proposed framework in other production environments with manual operations, such as re- and demanufacturing systems, u-shaped assembly lines, as well as human-robot collaborative settings.

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GIOVANNI LUGARESI is Assistant Professor at the Department of Mechanical Engineering of KU Leuven. His research interests include production planning and control, internal logistics, process mining, and robust optimization. His email address is giovanni.lugaresi@kuleuven.be.

KOVACS LASZLO is the head of Industry 4.0 Technology Center at the Budapest University of Technology and Economics. He worked as IT professional and held CIO positions in the telecommunication industry. He joined BME in 2018, where he is teaching IoT, industrial digitization, and participates in several industrial digitization research projects. His email address is kovacs.laszlo@vik.bme.hu.

KORNEL TAMAS is Associate Professor at Budapest University of Technology and Economics where he has received his M.Sc. and Ph.D. degrees. His professional field is the modelling of granular materials with the use of discrete element methods. His e-mail address is tamas.kornel@gt3.bme.hu and his web-page is http://tinyurl.com/korneltamas.