Safer and efficient assemblies: harnessing real time worker movements with digital twins

Satya Saravan Kumar Kasarapu[1*], *Gokula* Vasantha[1], *Adelaide* Marzano[1], *Jonathan* Corney[2], *Jack* Hanson[2], *John* Quigley[3], *Hanane* El-Raoui[3], *Nathan* Thompson[3], *Andrew* Sherlock[4]

[1]School of Computing, Engineering and the Built Environment, Edinburgh Napier University, Edinburgh EH10 5DT, UK
[2]School of Engineering, The University of Edinburgh, Edinburgh EH8 9YL, UK
[3]Department of Management Science, University of Strathclyde, Glasgow G1 1XQ, UK
[4]National Manufacturing Institute Scotland, University of Strathclyde, PA49LJ, UK

Abstract. This paper addresses a critical gap in digital twin simulation within manufacturing environments by focusing on the dynamic representation of worker movements during assembly processes. We introduce an innovative approach that utilises Ultra-Wideband (UWB) sensors to incorporate worker trajectory data into Siemens Process Simulate software, enabling the creation of a digital twin of assembly line operations. Our methodology involves comprehensive data collection using UWB sensors, followed by pre-processing steps such as data cleaning, interpolation, and classification of points into dwell and transit locations. Within the framework of Process Simulate, we develop the assembly process digital twin, integrating simulations of tricycle assembly alongside dynamic worker path and movement simulations. Our digital twin facilitates ergonomic analysis, process optimisation, and worker interaction analysis, offering insights for enhancing factory efficiency and safety. Notably, through visualisation of worker paths and identification of bottlenecks, our digital twin enables optimisation of resource allocation. Quantitative results demonstrate significant improvements, such as a reduction in the time of completion of six products by 11% compared to Discrete Event Simulation under similar process conditions. This study highlights the transformative potential of digital twin technology in manufacturing, providing a robust framework for simulating and optimising worker movements within real-world factory environments.

1 Introduction

In recent years, the manufacturing industry has experienced a notable shift towards digitalisation and automation, spurred by the principles of Industry 4.0. Central to this evolution is the concept of digital twins, virtual representations of physical assets or systems. Digital twins empower manufacturers to construct virtual models that accurately reflect the

* Corresponding author: s.kumar@napier.ac.uk

behavior, performance, and attributes of real-world counterparts in a dynamic and interconnected manner. This facilitates real-time monitoring, analysis, and optimisation of manufacturing processes, leading to heightened efficiency, productivity, and informed decision-making. Initially conceived in the aerospace and automotive sectors, the concept of digital twins has since permeated various industries, spanning healthcare, energy, and construction. The integration of advanced technologies like IoT, AI, and cloud computing has further propelled the adoption of digital twins across sectors.

Digital twins serve as a critical bridge between the physical and digital realms in modern manufacturing, enabling companies to create digital replicas of manufacturing assets, processes, and systems. This facilitates gaining valuable insights into operations, identifying inefficiencies, and optimising performance. With the global digital twin market projected to reach $48 billion by 2026, with a CAGR of 58%, their increasing adoption across industries is evident.[1] In manufacturing, digital twins are leveraged for product design, production planning, predictive maintenance, and supply chain optimisation. The ability to simulate and analyse intricate manufacturing processes in a virtual environment empowers companies to reduce costs, minimise downtime, and enhance product quality.

2 Challenges in replicating human movements in digital twins

The implementation of digital twins for human simulation and movement presents a myriad of challenges that must be addressed for effective utilisation in various domains. One significant challenge lies in achieving accurate and realistic representations of human movements, considering factors such as sensor accuracy and biomechanical modelling limitations [2][3]. Additionally, data latency and synchronisation issues hinder real-time responsiveness, leading to discrepancies between simulated and actual movements [4][5]. Integrating diverse data sources and technologies poses complexities due to compatibility issues and interoperability constraints [6][7]. Privacy and ethical concerns arise regarding the collection and processing of human movement data, necessitating safeguards for individual privacy rights [2][8]. Moreover, simulating human-robot interaction requires advanced modelling and control algorithms to achieve seamless collaboration and synchronisation [9]. Scalability issues, lack of standardisation, and best practices further impede widespread adoption, highlighting the need for industry-wide standards and guidelines [10][11]. Addressing these challenges through advanced modelling techniques, enhanced data integration capabilities, and ethical guidelines is essential to unlock the full potential of digital twins for human simulation and movement.

3 Methodology

3.1 Data collection and pre-processing

The need for dynamic tracking of people and goods within industrial sites has become increasingly crucial for enhancing performance and safety conditions. Traditional methods, such as door access control systems, are limited in their ability to provide real-time location data and often face challenges with unauthorised access and misplaced objects. To address these issues, we utilised Ultra-Wideband (UWB) tags and motion capture (MoCap) systems for accurate indoor localisation and tracking of personnel in an industrial setting. [12]

The assembly line setup consisted of six tricycle assembly rigs, each with specific assembly processes and fixed stations. Workers at each station performed designated tasks sequentially, leading to the assembly of six tricycles within a three-hour period. The industrial setup was designed to mimic real-world production environments, allowing for the collection of realistic worker movement data. It is important to note some key assumptions made during the study. The actual dimensions and weights of the tricycle are not known. As a result, a generic tricycle model was selected, and assembly operations were based on a standard assembly instruction booklet.

Each worker's path and actions were tracked using UWB tags placed in their pockets, providing precise information on their movements throughout the assembly process. The data captured included deviations from the predefined assembly protocol, such as breaks, or assistance provided to other workers. By analysing this data, insights into worker efficiency and process deviations could be gained, enabling opportunities for process optimisation and ergonomic improvements.

3.1.1 Data pre-processing

In this section, we describe the preprocessing steps applied to the data collected from Ultra-Wideband (UWB) tags attached to workers. The aim is to synchronise and organise the data to facilitate further analysis and simulation of worker movements in the assembly process. The data collected from UWB tags are recorded at intervals of 100 ms. To align the data and reduce noise, we convert the time interval to seconds, assuming negligible changes in worker positions within a second. We then apply a smoothing function by averaging the position data obtained within the same second. Missing data points, such as when signals are obstructed, are substituted with the worker's last known position.

Using the second-to-second dataset, we employ Hierarchical Dendrogram clustering to cluster data points into respective clusters for individual workers. We have selected hierarchical dendrogram clustering in comparison to K-means, DBSCAN, OPTICS, and Fuzzy C-means clustering due to a low Silhouette score and Davies-Bouldin Index, and high Calinski-Harabasz Index [13]. This assessment has adequately considered movement cohesion and separation between clusters. Points where a worker remains in a cluster for more than 10 seconds are classified as dwell points. Transit points are identified as the movement between dwell points. A continuous sequence of transit points provides the path for each worker. These steps are repeated for each worker to classify their respective dwell and transit points.

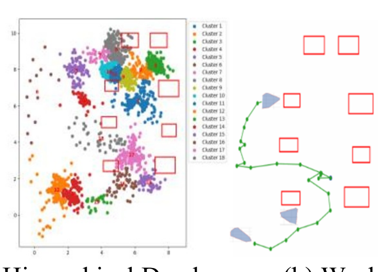

Fig. 1. (a) Clustering using Hierarchical Dendrogram (b) Worker Path and Dwell regions on the workplace.

3.2 Modelling digital twin for assembly process

3.2.1 Simulation in Process Simulate

Simulation in Process Simulate involves replicating the assembly process of the tricycle along with simulating worker paths and movements. This includes the execution of various tasks such as "Go," "Get," "Put," and "Push" actions by the workers involved. The simulation begins with modelling the assembly line layout and defining the process model of tasks to be performed. Each task corresponds to a specific action in the assembly process, such as mounting the lower frame, assembling the axle, attaching the saddle and pedal board, and so on. Process models were generated from the movement data using process mining techniques as outlined in Ayse et al. work [14]. In this step, the event log is utilised to discover a process model of the assembly process with a process mining algorithm.

To integrate movement data into Process Simulate and generate frames, we imported the movement data, which consists of second-to-second x, y coordinates of workers, as a CSV file in the form of MFG data points. Each point is created as a frame, and using the path editor, the sequence of transit point frames are used for creating the worker path. Utilising three-dimensional (3D) visualisation techniques, worker paths and movements are rendered in a spatially immersive environment, providing a comprehensive perspective of assembly operations. By visualising worker trajectories in 3D space as shown in Figure 2, alongside the assembly layout and equipment, this approach enhances the understanding of spatial relationships and ergonomic considerations. The simulation video can be accessed here.

Fig. 2. A pictorial depiction showcasing the tasks performed by workers during the assembly process and visualising continuous ergonomic assessment and worker interactions in the digital twin

3.2.2 Assembly of tricycle

In the tricycle assembly process model, each station is responsible for specific tasks. Station 1 builds the lower frame, passing it to Station 2, where the axle is assembled. Once completed, Station 2 transfers the assembly to Station 4. Meanwhile, Station 3 assembles the saddle and pedal board, also passing it to Station 4. At Station 4, the rear wheels and axle unit are integrated, then forwarded to Station 6. Simultaneously, Station 5 assembles the front wheel and axle unit, passing it to Station 6. Finally, Station 6 completes the tricycle assembly. Throughout the process, deviations from the protocol, such as breaks or assisting others, may occur, affecting stock replenishment and operator comfort. Figure 3 illustrates the sequence of assembly tasks involved in the process.

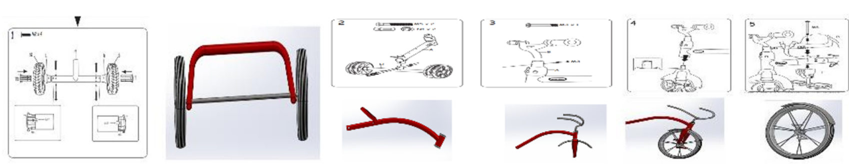

Fig. 3. Assembly tasks for the tricycle

4 Results and discussion

4.1 Ergonomic analysis

The digital twin developed in this study facilitates a comprehensive ergonomic analysis, allowing for the evaluation of physical strain and comfort levels associated with various tasks within the assembly process. Leveraging advanced simulation capabilities and real-time data integration, the ergonomic analysis encompasses multiple methodologies aimed at assessing and optimising worker safety and well-being.

The Static Strength Prediction (SSP) technique serves as a fundamental tool for evaluating the physical demands placed on workers during assembly tasks. By quantifying the forces exerted on the body in static positions, SSP analysis helps identify potential ergonomic hazards and inform the design of workstations to minimise the risk of musculoskeletal injuries. The static strength prediction analysis for Worker 4 depicted in Figure 4 (a) and (b) reveals that the trunk extension exhibits the highest value at 225.40 N, followed by the hip extension at 196 N, the knees flexion at 145.2 N each, and the ankles extension at 153 N. The knees and ankles experienced the moment of 11.4 and 39.9 Nm. These findings and highlight the distribution of forces across various body parts during the assembly tasks, providing insights into potential areas of physical strain and ergonomic concern.

Another method employed is the Rapid Upper Limb Assessment (RULA) [15], a rapid ergonomic assessment tool used to evaluate ergonomic risk factors associated with repetitive tasks and awkward postures. By assessing worker posture and movement frequency, RULA provides valuable insights into potential ergonomic issues and guides the implementation of interventions to mitigate risks. The assessment conducted using the Rapid Upper Limb Assessment (RULA), as depicted in Table 4(c), indicates a score of 2 for both left and right body parts, and a score of 1 for the trunk. This suggests that the operations performed fall within an acceptable risk level, with no immediate action required.

The analysis of generic joint angles with respect to time as shown in Figure 4(d) offers insights into the dynamic movements and postures adopted by workers during assembly tasks. Tracking joint angles throughout task execution helps identify ergonomic stressors and opportunities for optimising task sequences and workstations to enhance worker comfort and efficiency.

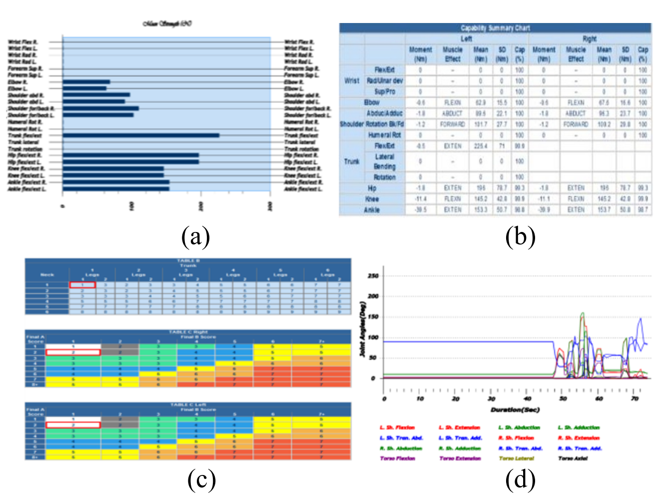

Fig. 4. (a) Static strength prediction (b) capability summary chart (c) RULA assessment chart (d) generic joint angle v/s time chart for worker 4.

4.2 Process optimisation

The utilisation of digital twin technology offers significant opportunities for optimising manufacturing processes by providing real-time insights into workflow dynamics and identifying areas for improvement. This section focuses on leveraging the digital twin framework to observe deviations from fixed task assignments and finding assignments based on data analysis, thereby enhancing process efficiency and productivity.

By analysing the event log within the digital twin environment, deviations from the predefined task assignments can be observed and analysed. For instance, it is noted that certain workers deviate from their assigned tasks, such as worker 2 joining worker 1 for task 1 initially, and worker 4 occasionally undertaking task 5. Additionally, worker 6 assists with tasks 2 and 3, indicating flexible task allocation strategies. These deviations may stem from task dependencies and the need for collaborative efforts to complete certain assembly stages. Incorporating the digital twin methodology, the worker's status (working or transiting) is determined based on their proximity to the workstation. When a worker is dwelling near the workstation, they are actively engaged in the assembly process. Conversely, when the worker is in transit, it is assumed that the assembly operation is temporarily halted, typically during product transfer between assembly stations. This integration enables real-time monitoring of worker activities and facilitates the identification of workflow interruptions or bottlenecks for proactive intervention. The box and whisker plots below in Figure 5 illustrate the completion times for assembling six tricycles. The data includes median completion times for both flexible and fixed allocations using Discrete Event Simulation (DES), sourced from Ayse et al.'s work[14]. Additionally, the completion time for the digital twin is calculated from the Minute-to-Minute report generated post-simulation in Process Simulate. This calculation involves summing the individual completion times for each operation associated with each worker. Notably, the assembly time for workers can be adjusted within Process Simulate by modifying the time allocated for each task. The median completion time for the fixed allocation DES is approximately 222 minutes, while it reduces to 211 minutes with flexible allocation. Similarly, the median completion time for the fixed digital twin is around 210 minutes, whereas for the flexible digital twin simulation, it's approximately 198 minutes. This indicates an 11.6% reduction in the median completion time for the fixed allocation DES compared to the flexible allocation using digital twin.

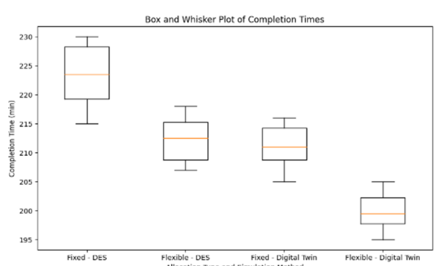

Fig. 5. Box and whisker plot for time of completion of six products.

4.3 Limitations

While Process Simulate offers a comprehensive suite of tools for simulating worker operations within a digital twin framework, there are several limitations that need to be addressed to fully leverage its capabilities in manufacturing environments.

One of the primary limitations of Process Simulate is the manual configuration required for setting up worker operations. Tasks such as "go," "get," and "push" need to be defined and programmed manually, which can be time-consuming and labour-intensive. This manual setup process restricts the scalability and agility of the digital twin, especially in dynamic manufacturing environments where operations may change frequently.

Another significant limitation is the lack of integration with real-time data sources. Process Simulate does not provide native support for automating operations based on real-time data inputs, such as worker location or task completion status. This limitation hinders the digital twin's ability to dynamically adjust operations in response to changing conditions on the factory floor, limiting its effectiveness in optimising workflow efficiency and resource utilisation. Furthermore, it's important to note that the assembly tasks are assumed for the present simulation which lead to present joint angles and Static Strength Prediction results. However, Process Simulate provides access to motion tracking software like Synertial [16] Full body mocap, enhancing its potential for realistic simulations.

Process Simulate currently lacks built-in functionality for easily exporting positional coordinates from external data formats, such as sensor data or motion capture systems. This limitation makes it challenging to integrate spatial data collected from other sources into the digital twin environment, hindering its ability to accurately simulate worker movements and interactions. Without seamless data integration capabilities, the digital twin may fail to provide an accurate representation of real-world manufacturing processes.

The existing automation options within Process Simulate are relatively limited, primarily relying on manual programming and configuration. While the software offers tools for creating and automating human operations, there is a lack of advanced scripting or code-based automation capabilities. Providing more options for automating human operations through custom scripting or code development would enhance the flexibility and adaptability of the digital twin, enabling more efficient and responsive simulation of worker activities.

5 Conclusion

In conclusion, the digital twin framework offers significant advancements in enhancing worker safety, productivity, and operational efficiency in manufacturing. By integrating ergonomic analysis and process optimisation methodologies, it enables proactive identification of ergonomic hazards, real-time monitoring of workflow dynamics, and immersive visualisation of worker interactions. However, challenges such as manual configuration, limited automation, and data integration need addressing for its full potential to be realised. Overcoming these hurdles will be crucial for maximising the benefits of digital twin technology in improving manufacturing processes and worker well-being. Additionally, it's worth noting that although Process Simulate primarily serves as a digital model [17], with some modifications, it can function as a digital twin by integrating real time data from motion tracker software. This capability enhances its potential to accurately replicate real-world manufacturing environments and further optimise worker operations.

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