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A step toward digital transformation: development of a compact bulk feeder digital twin to improve its functionality

Abstract

Increased global competition is intensifying pressure on companies such as Atlas Copco Henrob to enhance the performance of their products, including the Compact Bulk Feeder (CBF) component of the company's 'self-pierce riveting' machine. With the rapid advancement of digital technologies, there is an opportunity for Atlas Copco Henrob to leverage digitalisation to improve CBF functionality and gain a competitive edge in the market. This paper presents the outcomes of modelling the digital twin of the CBF which enables continuous monitoring and analysis of the CBF's performance. Focusing on enhancing its functional operation and capabilities. A comprehensive digital twin framework is introduced, incorporating suitable hardware for capturing and processing data, and software technologies to facilitate real time simulation and modelling that bridge the physical and virtual realms for two essential CBF functions. Additionally, the paper covers measuring the digital transformation performance at Atlas Copco Henrob.

Keywords: digital twin, digital transformation, industry 4.0

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Glyn Fargher,[1] Hugo Chester,[1] Ahmed Al-Ashaab,[2] Nik Fadilah,[2] Faiz Djafri,[2] Sai Nikhil Kumar Jaini,[2] Abdulaziz Aljumaiah[3]

[1]Atlas Copco, Deeside Industrial Park, UK
[2]Cranfield University, UK
[3]Doctor of Philosophy-PhD Manufacturing Engineering Technology, Cranfield University, UK

Correspondence: Ahmed Al-Ashaab, Cranfield University, College Rd, Cranfield, Wharley End, Bedford MK 43 0AL, Uk, Tel +44 1234 758465

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Introduction

The digital era, characterised by the emergence of Industry 4.0 (I4.0) enabling technologies, has triggered a paradigm shift in manufacturing companies' operations.[1,2] Organisations embrace digitalisation and the benefits of digital transformation to drive the development of smart manufacturing processes and intelligent products. These products are characterised by their connectivity, advanced features, and ability to leverage data for intelligent decision-making. Embracing these advancements can be the difference between organisations securing a sustainable competitive advantage and growth or facing rapid obsolescence.[3] Innovative companies, such as Atlas Copco Henrob, respond to the emerging influence of digital transformation across operations. Digital platforms and tools that drive seamless cross-organisation communication and knowledge sharing and encourage collaboration and creativity are being trialled and adopted across the organisation. Digital transformation provides a framework for enhancing innovation capabilities, allowing the company to capitalise on the collective intelligence and diverse expertise of professionals from various cultural and professional backgrounds to help deliver innovative products and organisational growth.[4,5]

In particular, Atlas Copco Henrob is actively directing its digital transformation efforts towards the research and development (R&D) department, recognising it as a critical area for innovation. Through the strategic selection, integration and optimisation of specific I4.0 technologies throughout the product development (PD) value chain, digital transformation empowers R&D teams to identify and extract valuable insights from previously untapped data sources. This transformative approach is revolutionising the company's traditional PD practices, enabling the optimisation of 'smart' processes to develop 'smart' connected products. One implementation of digital transformation at Atlas Copco Henrob involves a research project centred on creating a digital twin of their new compact bulk feeder (CBF) product—a critical component of their self-pierce riveting (SPR) platform. This pioneering initiative marked the company's first venture to create a virtual representation of a physical product. By leveraging the opportunities digital twins enable, engineers could efficiently assess product performance, conduct extensive scenario testing, and rapidly optimise system functionality based on insights derived from Failure Mode Effect Analysis (FMEA). This data-driven approach resulted in significant reductions in PD time and costs, expediting the time-to-launch of the product and enhancing its compatibility with smart-connected factories. This research attempts to answer whether the enabling technology of digital twins can address some of the identified operation problems via FMEA application analysis. Moreover, this research aims to assess and guide these digital transformation efforts, and the developed Digital Transformation Performance Measurement Tool was implemented within the R&D environment. The tool incorporates four perspectives: digital transformation processes, smart data environments, autonomous and automated resources, and people and skills. This evaluation framework facilitates a comprehensive and nuanced assessment, ensuring a holistic approach to digital transformation strategy and implementation. Another question this research seeks to answer is howto measure a company's digital transformation readiness.

The research consisted of four phases. Phase one reviews the related literature and investigates digital twin technologies. Phase two applies the Digital Transformation Performance Measurement Tool within the R&D department and performs a detailed analysis. Phase three consists of four critical tasks:

1) Identifying CBF design and operational issues,
2) Implementing the right digital twin technologies,
3) Defining the physical-to-virtual world flow, and
4) Developing the digital twin model of the CBF. Phase four validates the work via a case study, evaluates the results via expert judgment from the company, and finally discusses the evolving digital twin work of the CBF. This paper expands upon

earlier work presented at the 2022 4th International Conference on Industry 4.0 and Smart Manufacturing,[6] which forms the basis for the developments discussed.

Literature review

Digital transformation performance measurement

In manufacturing, digital transformation involves leveraging Industry 4.0-enabling technologies to shift from traditional manufacturing processes to intelligent and interconnected systems.[7–9] This transformation enhances operational efficiency and product quality, accelerates innovation and product development, reduces operational costs and resource optimisation, fosters agility and adaptability, and improves customer experience and interaction.[7,10]

However, digital transformation is more than implementing modern technology, investing in tools, or upgrading existing systems.[7] Instead, it requires a broader approach encompassing a comprehensive strategic business model, resources, capabilities, and technologies as key drivers of the transformative process.[5] The critical phases of the digital transformation process are as follows:

a) **Establishing vision and objectives**: Companies need to formulate a vision and objectives to guide the development of digital transformation initiatives.[11]

b) **Evaluation of technological infrastructure**: Assessing technological infrastructure, systems, software applications, and tools to address organisational manufacturing needs.[9,12]

c) **Designing end user and employee experie**nce: Prioritises customer experiences and the introduction of new capabilities.[7]

d) **Reviewing and Selecting Appropriate Solutions and Vendors**: Comprehensive evaluation of solutions from various technology providers.

e) **Formulating a Roadmap**: Compiling business objectives, projected experiences, digital technologies, and solutions to form an actionable plan.

Maturity models are crucial in helping organizations assess their position and progress in any transformation journey.[13] By evaluating selected concept-specific metrics, they guide companies to conceptualize and measure their current level of maturity or readiness compared to a future desired level, identifying strengths, weaknesses, and opportunities to performance manage this journey.[14,15]

Researchers at Cranfield University have developed a Digital Transformation Performance Measurement Tool, or 'Maturity Model,' to evaluate a company's readiness and maturity for digital transformation, including initiatives such as digital twins. This tool comprehensively assesses a firm's digital capabilities from multiple perspectives, offers insights, and provides actionable recommendations for management to priorities areas that require attention and investment. To rigorously assess the tool's effectiveness and industry relevance, it underwent comprehensive evaluation within Atlas Copco Henrob's digital twin research project, providing a real-world framework to verify its capabilities and applicability.

Review of digital twin-related literature

Digital twins have gained significant attention in industry and academia as part of the broader range of I4.0 techniques and enabling technologies. However, a unified understanding and precise definition of digital twins are lacking because of their unique and emerging nature. Given the flexibility of this technology, digital twins can be applied in various ways, as Jones et al. (2020) noted. According to the reviewed literature, digital twins can be defined as:

a. Integrated multiphysics, multiscale, probabilistic simulation of a complex product, which functions to mirror the life of its corresponding twin.[16,17]

b. A virtual representation of a real object in which data exchange occurs between the digital and physical worlds.[18]

c. Effortless integration of data between a physical and a virtual machine in either direction.[19]

Digital twins can, therefore, be best described as virtual representations of objects involving bi-directional data exchange, that is, to and from the physical and virtual worlds.

Four types of generic digital twin reference models have been identified in the literature: three- and five-dimensional models, hierarchical models, and life cycle models, which provide a foundation for digital twin applications while allowing flexibility in implementation.[20] The widely used three-dimensional model focuses on the interaction between physical and virtual spaces, and the five-dimensional model adds data and service dimensions for enhanced functionality.[18] Hierarchical models organise digital twin elements into layers to facilitate information exchange across different levels of manufacturing operations.[21] Life-cycle models link information across various product and manufacturing phases, emphasising the integration of design, monitoring, and optimisation processes.[22]

Classification by researchers grouped digital twin services into product customisation, visualisation, monitoring, and optimisation. Product customisation services, such as geometric variation management and assembly planning, lever-age digital twins to adjust manufacturing strategies in real-time and enhance product quality and maintainability.[23,24] Visualisation services employ graphical tools and 3D interactive models to facilitate the understanding and control of manufacturing processes.[25] Monitoring services focus on tracking machinery behavior and product quality using digital twins for predictive maintenance and quality assurance.[26] Optimization services, including virtual commissioning and parameter optimization, aim to improve manufacturing efficiency and sustainability through data-driven decision-making.[27,28]

Digital Twin content includes models, data, and communication technologies crucial for digital twins. Models are categorised into geometric, physical, behavioural, and rule-based types, each serving distinct functions within digital twins. Geometric models visualise physical entities through athematical formulations.[29] Physical models, divided into first-principles, data-driven, and hybrid models, encapsulate the underlying physics of machines and processes.[30,25] Behavioural models, including flow and state models, describe system responses to environmental stimuli and facilitate understanding system dynamics.[21] Rule-based models, derived from learning-based techniques or expert knowledge, enable digital twins to reason, evaluate, and make autonomous decisions.[31]

Communication protocols ensure that the data and control commands are accurately exchanged between the physical and virtual entities. Protocols such as the OPC Unified Architecture, Message Queuing Telemetry Transport (MQTT), and MTConnect are pivotal for data exchange, offering unique capabilities for bidirectional communication and data management.[32]

Database systems and ontology models provide infrastructure for storing and organising vast amounts of data generated by digital twins. While relational databases offer structured data management using SQL, non-relational (NoSQL) databases tailor unstructured data and provide flexibility in data handling.[33] Cloud technologies further support digital twin scalability and accessibility, with considerations for data security and latency. Ontology models, defining terminology and relationships between data types, enhance the semantic richness of data and support interoperability and consistency across digital twin systems.[34,35] Protégé Editor and semantic web frameworks facilitate the creation and operation of ontology-based digital twins, improving data interoperability and analysis.[36,37]

The reviewed literature clearly showed the need for a simplified framework to introduce and provide step-by-step guidance to achieve an accurate digital twin implementation.

Digital transformation performance measurement case study: atlas copco henrob

Kaplan and Norton's Balanced Scorecard inspired the Digital Transformation Performance Measurement Tool at Cranfield University.[38] The tool incorporates four balanced dimensions or perspectives, assigning an equal importance of 25% to each dimension. Based on the literature review, these perspectives were carefully selected to address key strategic management issues associated with effective digital transformation in manufacturing companies. Within each perspective, the tool uses eight questions to assess the various aspects of digital transformation. These questions were structured using a five-level SMART scale comprising five levels, as depicted in Figure 1.

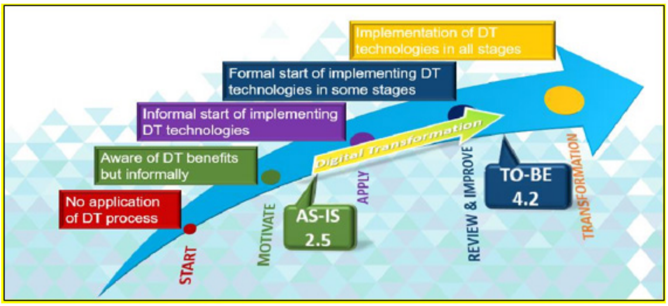

Figure 1 Overall AS-IS and TO-BE results of digital transformation performance measurement of Atlas Copco Henrob and the illustration of maturity levels and their meanings.

Baslyman.,[39] highlighted that the central elements of digital transformation are processes, data, hardware, and people. The authors believe that the first step in measuring readiness toward digital transformation is to provide management support and have the right transformation processes.[8,40] Hence, the first perspective is 'Digital Transformation Processes'. Digital transformation addresses the data and hardware of cyber-physical systems in industrial manufacturing processes to establish intelligent, self-regulatory, autonomous, and interconnected value creation. The second perspective is 'Smart Data Environment', and the third is 'Autonomous and Automated Resources'.[9,12,41] The people aspect focuses on cultivating the right culture to enhance the efficiency of digital transformation and create an awareness of its benefits. In addition, skill is tacit knowledge that employees must have to do the right job. The fourth perspective identified is 'People and Skills'.[42]

The four perspectives covered by the tool are summarised as follows.

a) **Digital transformation processes**. This perspective evaluates current efforts, tangible benefits, and understanding of digital transformation processes and challenges.

b) **Smart data environment.** This perspective delves into the data-related aspects of digital transformation, encompassing IoT applications, AI, cybersecurity, digital twins, clouds, and big data analytics.

c) **Autonomous and automated resources**. This perspective assesses the simulation of the hardware, advanced robotics, and autonomous applications used in manufacturing.

d) **People and skills**. This perspective measures people's hard and soft skills in leading digital transformation initiatives and implementing related I4.0-enabling technologies.

As discussed, Atlas Copco Henrob's R&D department is in the initial stages of digital transformation. It is developing a digital twin of its CBF product to improve product testing, system functionality, and compatibility with smart-connected factories. This context offered an optimal setting for evaluating the organisation's digital transformation maturity.

The case study involved four engineers from across R&D who provided insights from all perspectives. However, only the overall result and outcome of the Smart Data Environment perspective are presented in detail here. The overall result (Figure 1) indicates that the company scored an average of 2.5 out of 5, illustrating an awareness of the benefits of digital transformation and limited implementation of various Industry 4.0-enabling technologies in isolated applications.

Further analysis of the Smart Data Environment perspective, as shown in Figure 2, reveals the following:

Q 1	Analysis of IoT applications in products	3
Q 2	Smart Products based on IoT	2.5
Q3	Analysis of AI implementation	2.75
Q4	Analysis of cybersecurity techniques implementation	3
Q5	Analysis of digital twin implementation	2.25
Q6	Analysis of deployed applications in cloud platform	2.5
Q7	Cloud computing platform	2.75
Q8	Analysis of big data analytics implementation	2.25

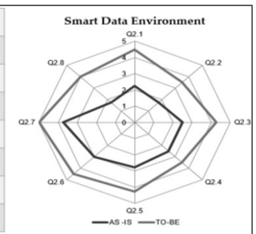

Figure 2 Results for 'smart data environment' perspective of Atlas Copco Henrob.

a) **Analysis of IoT applications on products (2.25):** indicating efforts to design and produce future IoT-based products.

b) **Current products with IoT applications (1.75):** indicating the absence of such applications.

c) **Formal analysis and implementation of AI (2.5):** suggesting a relatively high score due to understanding AIenabling technology.

d) **Application of cybersecurity techniques (2.5):** reflecting a relatively low score as the company's IT fully complies with cybersecurity protocols, but customers handle product implementation.

e) **Formal analysis and implementation of digital twin applications (2.75):** indicating the company's initiation of analysing the application of digital twins in specific R&D projects, such as the one discussed in this paper.

f) **Various cloud applications:** 3, encompassing CAD applications and sharing test results for several products.

g) **Selection and implementation of the appropriate cloud computing platform (3.75):** reflecting a successful implementation.

h) **Analysis of where Big Data Analytics could be applied (1.75):** highlights room for improvement and significant potential.

CBF digital twin development

CBF Overview and Operation

Figure 3 describes the CBF and its critical parts. The operating sequence of the CBF ‘is as follows:

1) The hopper is manually loaded with rivets, serving as storage for the fasteners.
2) The hopper gate oscillates, allowing the rivets to descend into the bowl.
3) The bowl vibrates at a specific frequency, causing the rivets to move along the track.

Note: The vibration frequency remains constant and does not change with the mass of rivets in the bowl.

4) The track aligns the rivets into the correct orientation before they enter the escapement.
5) Rivets improperly oriented in the track are blown back into the bowl through the ‘side blow’ mechanism.
6) The ‘recovery blow’ mechanism blows any rivets stuck in the track back into the bowl.
7) The escapement stores a predetermined number of rivets and guides them into a tube that transports them to the riveting gun tool.

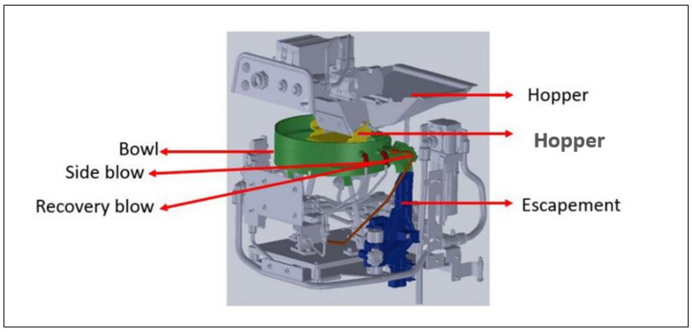

Figure 3 CBF sub-systems.

One risk identified via DFMEA is the irregularity of bowl vibration that can lead to an overflow of rivets, failing to feed them from the bowl into the track. This feed failure leads to poor performance of the CBF. A digital twin of the CBF was created to address this risk, allowing for control of the hopper and bowl function.

The network depicted in Figure 4 visually represents the physical CBF shown in Figure 6, facilitating decision-making to resolve operational issues and improve productivity. In the virtual model, an overlay text displays either the number ‘1’ when enough rivets are present or ‘0’ when there is an insufficient number. Based on this reported state, the hopper mouth in the virtual world is either open or closed. Once the connection between the virtual and physical worlds is established, the physical model behaves like the virtual model.

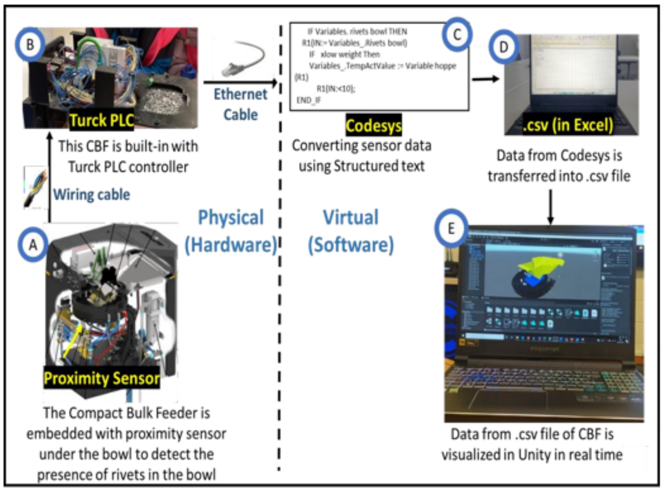

Figure 4 Physical to the virtual world, digital twin development of the CBF.

The following has been achieved by the application of a digital twin of hopper and bowl that increases the hopper and bowl function performance:

a) The level of the rivets in the bowl was visualised using data collected from a proximity sensor.
b) Feedback to control the movement of the hopper gate after receiving proximity data from the physical world.

Definition of digital twin framework

The case study of the CBF involves defining a Digital Twin framework, as illustrated in Figure 4. This framework in-corporates carefully selected digital twin technologies to create a suitable environment for simulating the functionali-ties and behaviours of the CBF in the virtual world. The framework is explained as follows:

a) Ensure accurate data capture by selecting the appropriate sensor. In Figure 4A, the existing proximity sensor is utilised to capture real-time data at the rivet level in the CBF bowl. Alternative sensors, such as weight or accelerometers, are considered but dismissed due to sensitivity concerns.
b) The sensor data are read by configuring the controller, as shown in Figure 4B. The existing programmablelogic controller (PLC) of the CBF can read the sensor’s input (high/low).
c) The controller data were transferred to a local laptop/PC for analysis. As shown in Figure 4C, the Turck PLC can be programmed using the Codesys software to govern data capture and transfer via an Ethernet cable.
d) The local PC serves as an offline system.
e) The captured data are stored in a database. A local file with a .csv extension on the PC, depicted in Figure 4D, serves as a database for storing the captured data. Simulate and visualise the physical behaviour of the hopper and bowl using system software. Figure 4E shows the system software selection as an advanced real-time 3D creation platform. System software offers extensive learning pathway documentation and is suitable for simulation and visualisation development.[43]
f) Choose a programming language to instruct on the solution. According to a study by Andrist et al.,[44] C# scripts can be written and executed within the system’s software to control the objects

in the program. A specific C# script must be written to affect the solution in the physical world, as shown in Figure 5A.

g) The instruction data were stored in the database. As in Step 4, a local file with a. The .csv extension on the PC serves as a database (Figure 5B) for storing instruction data before being imported by the controller.

h) Transfer the data from the local laptop/PC to the controller. An Ethernet cable was used as the medium for data transfer, and Codesys software was employed to instruct the actuator actions (Figure 5C). A local PC functions as an offline system.

i) The control hopper and bowl actions were performed using the existing Turck PLC as the controller (Figure 5D).

j) To optimise the hopper and bowl functions, actions are performed to enhance the device performance and efficiency by controlling the existing hopper pneumatic cylinder (Figure 5E).

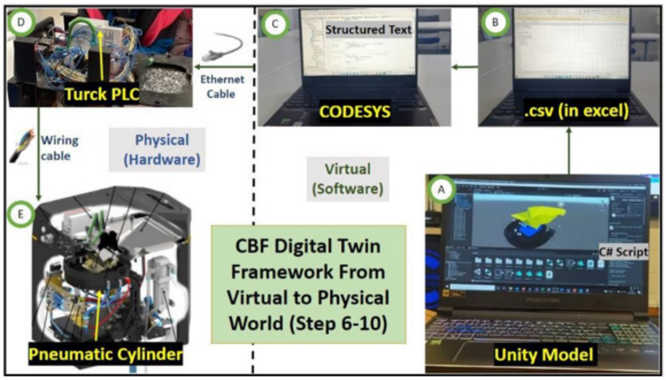

Figure 5 CBF digital twin (**virtual** to the physical world).

The CBF digital twin development

A digital twin simulation of the CBF hopper and bowl function was systematically constructed through a structured methodology within the framework of the CBF case study and tested in lab environment to optimise system performance and facilitate comprehensive analysis:

1) A 'proximity sensor' is installed to capture real-time rivet-level data on the bowl of the CBF. This sensor was integrated to improve hopper and bowl function performance.

2) The proximity sensor's address was identified by referring to the electrical wiring diagram and visually checking the cable wires within the Turck PLC's I/O port.

3) The IEC61131-3 programming language was used to write the code to capture the proximity sensor data.

4) The captured data were stored in a database using the Codesy OPC configurator function. This function involves adding a symbol configuration in the Codesys program tree to assign the proximity sensor data as a variable and connecting the OPC office link function to export the data to an external file in .csv format.

5) The Unity open-source software was used to simulate and visualise the performance of the CBF hopper and bowl functions. This step involved utilising the 3D CAD model of the hopper and bowl developed in Solid Edge and exported in STEP format to ensure compatibility for importing it into Unity software using the Pixyz plugin.

The setting parameters of Unity software simulated the behaviours of the hopper and bowl. These parameters include mass, gravity, movement boundary, collision boundary, impulse property, and damping property of the rivets, hopper, and bowl. Boundary conditions were set to represent the properties of the actual physical CBF and rivet elements, such as mass, elasticity, and damping properties. A convex boundary function of the Unity software was set up to represent the interactions between CBF and the rivets in the bowl.

The following work was conducted to develop the digital twin from the virtual to the physical world, as shown in Figure 5.

A. A C# script within the Unity software was written to control the hopper and bowl functions of the CBF by opening or closing the hopper mouth to control rivet feeding.

B. A C# script was written in the Unity software to export the data in .csv format on a local computer. This script was integrated into the C# script from the previous step.

C. The coding of the C# script for the data transfer process from .csv file to 'structured text file' was written to transfer the instruction data (using TCP/IP Communication Protocol) from the local PC to the controller 'Turck PLC', as shown in Figure 5D.

D. The address of the proximity sensor was determined by referring to the electrical wiring diagram of the system and visually inspecting the cable wires within the I/O port of the Turck PLC.

E. The hopper and bowl function performance was controlled by opening or closing the hopper mouth to regulate the feeding of rivets based on the simulation of the virtual world using the Unity software.

The following are the criteria for selecting DT technologies:

a) 'Unity' is an open-source software used as an advanced real-time 3D creation platform that can be used as a system to design games or app scenes in 3D. Unity also has extensive learning pathway documentation that can be freely accessed to support the development of simulation and visualisation.

b) 'C# Script' can be written and executed inside 'Unity' software to control objects created inside the Unity model.

c) Specific 'C# Script' must be written to instruct the right solution in the physical world.

d) 'Codesys' is software that instructs data capture and transfer. The CBF has a 'Turck PLC' that can be programmed using 'Codesys' software.

The digital twin model of the final CBF product is shown in Figure 6. In the virtual model, monitoring the change in rivet-level amount is possible. The rivet level amount is checked and monitored, and the hopper mouth changes are triggered (labelled in blue).

The evolving digital twin work of the CBF

The digital twin research on the CBF raised several key questions:

Could bowl vibrations be simulated?

The research compared Unity and Unreal Engine simulation engines for bowl vibration. While Unity has been predominantly used in this research due to its ability to read real-time data from multiple storage formats, including CSV files, it demonstrated limitations in accurately simulating bowl vibrations. In contrast, Unreal Engine (https://www.unrealengine.com), an advanced alternative to Unity, exhibited superior visualisation capabilities and more accurate simulation of bowl vibrations. However, Unreal Engine cannot directly read data from external storage, requiring manual input or preloading. Ongoing research aims to integrate this functionality in the next release of Unreal Engine, potentially combining its superior simulation capabilities with the data accessibility features of Unity. This development could significantly enhance the overall effectiveness of bowl vibration simulation in future studies.

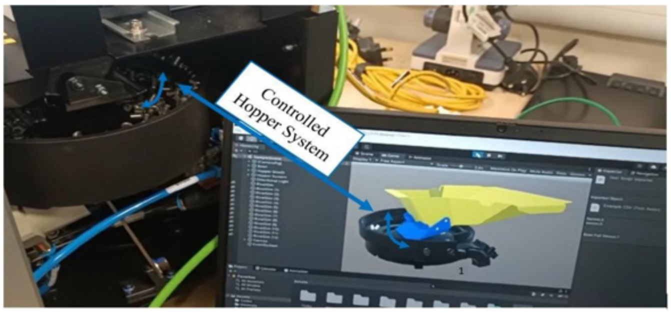

Figure 6 The digital twin of the CBF – Real-time visualisation in Unity.

Could the rivet movement be accurately simulated in the bowl?

A better simulation of the rivet moments in the bowl would require computer-aided engineering (CAE) software that can be embedded in the digital twin framework. This simulation would require more computer programming with the CAE software Ansys Twin Builder (https://www.ansys.com/digital-twin). The following are the steps are recommended that are shown in Figure 7:

a) Acquire ANSYS Twin Builder, (Figure 5–7).

b) Import the CAD model of CBF, including the rivets, into ANSYS (Figure 5–7).

c) The bowl vibration behaviours were simulated by setting the parameters in ANSYS.

d) Bowl vibration interactions are added between the rivets and CBF elements.

e) Run the simulation.

f) The results of the bowl vibration are transferred into the cloud by writing JavaScript (.json format) (Figures 4–7).

g) Import the bowl vibration data from the cloud to the real Engine using C++.

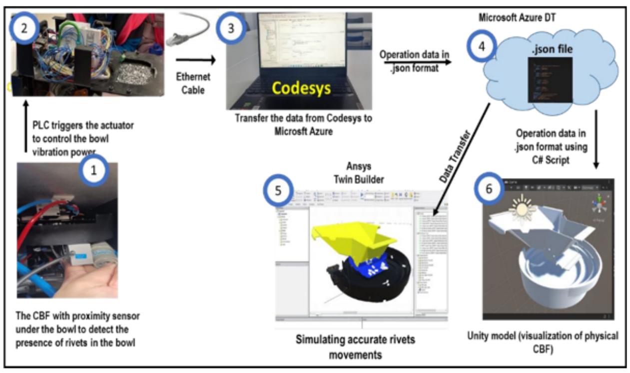

Figure 7 The future development of the digital twin of the CBF using Ansys Twin Builder.

Bowl degradation could be simulated and monitored using a digital twin

The repeated movement of rivets over time will degrade the bowl's surface finish. Simulating bowl degradation could prove advantageous; however, an additional sensor would be installed, although this would add further load to the bowl, affecting its performance and effectiveness. The steps required to introduce this capability are as follows.

1) Paint the bowl and tracks of the CBF and measure how much paint is degraded using photo-sensing devices

2) An accelerometer measures the vibration profile to determine if the bowl vibrated according to the instructions (e.g. 70 Hz). The vibration frequency and profile will be affected if any part of the bowl wears away.

Conclusion

Digital transformation performance measurement

Increased international competition is compelling companies, including Atlas Copco Henrob, to transform by adopting initiatives like digital transformation and identifying innovative ways, such as digital twins, to improve processes and products. Such transformations are challenging to plan and execute effectively, and tools and techniques that support this change to be performance-managed are welcome. This case study provided valuable insights into the efficacy of Cranfield University's performance measurement tool and the digital transformation maturity of Atlas Copco Henrob's R&D function, particularly concerning the Smart Data Environment perspective and the benefits of initiatives such as digital twins. These findings contribute to a deeper understanding of the company's current state and offer opportunities for further enhancement in its digital transformation journey.

Learnings from the performance measurement study are twofold. First, developing a performance measurement tool based on the Balanced Scorecard approach has provided a structured and systematic way to evaluate digital transformation readiness and progress and a comprehensive assessment of critical aspects of digital transformation. Second, the practical application of the tool in the Atlas Copco Henrob case study demonstrates its utility and relevance in evaluating digital transformation maturity, particularly from a Smart Data Environment perspective.

By applying this performance measurement tool, researchers and practitioners can obtain a comprehensive and balanced assessment of the readiness and progress of manufacturing companies in their digital transformation efforts. This analysis contributes to a theoretical and practical understanding of effective strategies and practices for successful digital transformation in the manufacturing sector, ultimately contributing to long-term success in the digital era.

Digital twins

By creating a digital twin of the company's CBF, a virtual representation of a crucial component in the platform, real world data was used to continuously update and enhance the twin, enabling simulation and reasoning for decision making. A potential operational issue was identified, visualised, and resolved through simulations and experiments that involved adjusting various CBF parameters, leading to an improved configuration. The key findings of this study include:

1) This project has been instrumental in identifying an industrial application for digital twins and assessing the capability of digital twin technologies to address potential design and operational challenges.
2) Integrating various hardware and software technologies is crucial for performing and creating digital twin modelling and simulations. Establishing a well-defined framework to facilitate the flow of digital twin activities from the physical to the virtual world is essential, as depicted in Figure 4.
3) Creating accurate digital twin models and simulations requires careful consideration of data capture sensors that can effectively represent the digital twin and accurately reflect the behaviour of the physical product. Additionally, establishing a reliable real-time connection for implementing recommended actions poses a signifi- 385 cant challenge in digital twin applications.
4) The successful simulation and visualisation of the hopper and bowl function achieved by utilising digital twin technologies in this project is a solid foundation for further work.

Although digital twins have contributed significantly to achieving this project's objectives, several challenges remain. The most notable difference between the digital twin and the 3D model is that the digital twin can visualise the behaviour of the physical object together with the interactive visualisation data synchronised in real-time with the operational data for the design. However, this CBF case involves the movement of rivets, which are random and challenging to replicate in the virtual world.

As the CBF bowl vibrates, each rivet moves independently from the centre of the bowl to the track, allowing it to escape to the riveting gun. It is doubtful that the rivets will move precisely as the actual object in the virtual world. As a result, the test run in the virtual world will not be as accurate as that in the physical world because of this limitation.

In addition, the CBF does not support preventive maintenance because it lacks a sensor to collect the relevant data. Over time, the bowl's track will degrade due to fatigue stress caused by the friction between the rivets and the bowl. As this happens to the CBF, the virtual world will be unable to visualise this since its design cannot monitor such defects, causing a discrepancy between the physical and virtual worlds.

Having the correct DT framework is essential for effective DT applications. Understanding current operational and design issues is vital to provide a scenario in which DT-enabling technologies can address these issues. Studying the current capabilities of the DT infrastructure of a product is essential for accurately applying DT scenarios. The presented work of the DT on the CBF (Figure 4) (Figure 5) could be generalised to other vibrators, with attention paid to the customisation that would be needed case-by-case. Digital transformation of enterprise could not be achieved without real hands-on knowledge of the applications of the enabling technologies of Industry 4.0

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Conflicts of interest

The author declares that there are no conflicts of interest.

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