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An Artificial Intelligence Driven Digital Twins Framework for Reconfigurable Manufacturing Systems: Towards Integration, Adaptability and Productivity

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Abstract

Reconfigurable Manufacturing Systems (RMS) are being utilised in smart manufacturing due to its ability to rapidly adjust its functionality and production in line with changes or fluctuations in market demands. The integration of Artificial Intelligence (AI) with Digital Twin (DT) offers a robust capability for real-time system's configuration, predictive analytics, process optimisation and decision-making in RMS. This study proposed an AI-DT framework for RMS to enable intelligent reconfiguration, adaptive control, continuous monitoring and machine learning (ML)-based predictive analytics. First, systematic literature review was employed to synthesis existing literature on the applications of AI and DT to identify research gaps and foster their integration within the RMS environment. Secondly, a framework that leverages AI, Internet of Things (IoT) and cloud computing was proposed to process high-volume sensor data to enable effective system's reconfiguration in real time. The validation of the proposed AI-DT model conducted in the Python environment indicated that the model can achieved up to 35% increase throughput and 55% reduction in downtime compared to the baseline model. Furthermore, the proposed intelligent model achieved 48% improvement in response time compared to the baseline. The findings obtained in this study suggest that integrated AI-DT model can significantly promote the agility and resilience of RMS in smart manufacturing. The findings of this study are useful in the exploration of AI-DT models for enhancing the capabilities of the RMS.

Keywords: Artificial intelligence, Digital twin, Internet of things, Machine learning, Reconfigurable manufacturing systems

1. INTRODUCTION

The growing manufacturing systems requirements necessitate the need for a time and cost-effective manufacturing solutions that are data-driven, dynamic, effective and responsive to manufacturing dynamics and market changes [1–3]. This is because of the increase in the global market competitiveness coupled with technological advancement. The evolution of reconfiguration to enable manufacturing systems to rapidly respond to market dynamics is gradually gaining increasing acceptability and momentum especially in manufacturing industries who seek innovative systems that are adaptive, responsive, scalable, and flexible to accommodate the various production needs and market dynamics. The manufacturing trend globally suggest that it is becoming increasingly dynamic due to product customization and variety, fluctuating demands and market volatilities, hence, the need for an intelligent manufacturing system. The conventional manufacturing systems are mostly not data-driven thus lack the required adaptability and flexibility to effectively respond to market dynamics in real time. Sometimes, the responses are slow often characterised with high set up time and system's downtime thereby contributing to the costs of manufacturing. This challenge can be addressed by the utilization of the Reconfigurable Manufacturing Systems (RMS) which offers scalability, modularity, adaptability, flexibility, and rapid reconfiguration capabilities. Artificial Intelligence (AI) is an enabling technology that can provide machine learning-based predictive analytics to make informed decisions about manufacturing systems in real time while the Digital Twin (DT) creates a digital replica of the physical systems, thereby enabling real-time simulation, monitoring, and prediction of the manufacturing systems. When integrated with AI, DTs can analyse vast amounts of sensor data, predict system behaviour, and continuously monitor system's performance with recommendation to implement optimal reconfigurations.

AI-DT integration will enable the evolution of DT from a passive simulation model into an intelligent, self-learning system with optimised configurations capable of predictive analytics, autonomous monitoring and decision-making. This study proposes an AI-driven DT framework for RMS that integrates Internet of Things (IoT), data, edge-cloud computing, and machine learning models to enable adaptive reconfiguration with minimal downtime.

Digital Twins (DTs) are virtual replica of the physical systems which integrates simulations and data analytics. RMS are systems that are adjustable to meet the current market or production demands. It is designed for a quick change in structure, functionality, hardware and software components to enable the adjustment of production capacity in response to sudden changes in market requirements [4]. RMS operated based on six major principles: modularity, scalability, integrability, convertibility, diagnosability, and customization [5–10]. These principles are intertwined into sustainability principles within the larger context of eco-friendly manufacturing. However, for RMS to operate as designed, there is a need for enabling technologies for its monitoring, data analysis, and optimization of its dynamic behaviour in real-time. The AI and DT are transformative technologies and enabler of smart manufacturing. AI enhances predictive analytics while DT can act as a virtual replica of a manufacturing system enabling real time monitoring, simulation, optimisation and decision making with changes in market demand changes. The AI-DT can enable rapid and easy configuration of RMS by the virtue of simulation and testing thereby enabling the system to become more flexible, adaptive, agile and responsive to manufacturing requirements. The use of the AI and DT as a separate technology for enhancing smart manufacturing has been reported [11, 12]. Onaji *et al.* (2022) [12], proposed a conceptual framework that enables the product-process integration via DT to enable a seamless manufacturing process flow throughout a product development lifecycle. Shao and Helu (2020) [13], identified some major requirements of DTs in smart manufacturing applications. The authors indicated that DT systems must be generic, reusable, and customizable to enable support for various use cases a diverse range of pertinent use cases, including a detailed methodologies to ensure best practices in its deployment. To ensure effective data handling in smart manufacturing Redelinghuys *et al.* (2020) [14], proposed a DT that facilitates exchange of data between the virtual and physical systems in real time. The proposed system comprises local data layer, IoT, cloud computing and simulations layer. Cimino *et al.* (2019) [15], applied DT in a Manufacturing Execution Systems (MES) integrated with assembly line. The study demonstrated the possibility to control the physical system within a MES with the aid of the DT. Even though, DT has been widely implemented in smart manufacturing, it still remains an interesting field of research because of its potentials. Existing studies had focused more DT modelling and simulations and data integration with little efforts in the areas of integration with machine learning algorithms for predictive analytics and optimisation, [11–15]. The use of AI in smart manufacturing for demanufacturing operation, diagnostic and predictive maintenance, improving product's functionality and performance and in manufacturing resilience have been reported. For instance, Gholami *et al.* (2024) [16], demonstrated the use of AI model integrated with fuzzy logic systems to determine how input variations affect decision outcomes and system's performance in RMS.

This study contributes to the advancement of AI-DT integration tailored towards smart manufacturing specifically RMS. It addresses the integration of AI-DT and the intersection of this integration with RMS and contributes to AI-DT Implementation geared towards RMS. It also highlights the need for a consolidated understanding of the current state of the art in this domain.

2. SYSTEMATIC LITERATURE REVIEW

2.1 Summary of Reconfigurable Manufacturing System

Recent manufacturing requirements indicate that inflexible systems are gradually phasing out giving room for a more flexible and adaptive systems that can respond effectively to changes both in structure and in functions [17–19]. Recently the development of some reconfigurable systems has been deported across various industries. For instance, the reconfigurable vibrating screen (RVS) finds application for particle screening in the mining industries [10], the reconfigurable assembly systems (RAS) for rapid assembly operation [5, 9], the reconfigurable guillotine shear and bending machine for sheet metal cutting and bending [7], reconfigurable assembly fixture (RAF) for holding workpiece for low-weight machining [8], amongst others. These systems show capability for meeting the goals of reconfiguration such as real time flexibility and adaptability that enable effective response to changes as demand changes, modularity, and scalability etc. The modularity goal of system's reconfiguration enables modular components to be added or removed from the system as production demand changes. Scalability permits the system's capacity to be scaled up or down without the need for redesigns. RMS are also convertible which implies that they have the ability to produce different variants of products. Their diagnosability enables effective monitoring so that failures or errors could easily be detected and resolved to minimise downtime while their integrability enables the integration of hardware or software components to improve the system's performance Finally, RMS are also customizable enabling them to be deployed to meet specific or custom customers' needs.

FIGURE 1, displays the principle of reconfiguration and the major components and requirements for the deployment of DTs in RMS. Some of the requirements include the presence of virtual and physical, data acquisition and processing systems, data sharing and storage platforms, computing infrastructure as well as ML algorithms and user's interface. Although, the framework is generic but can be modified to suit the individual need of the various manufacturing industries based on their capabilities. The framework shows capacity for continuous monitoring and improvement, process optimisation, predictive maintenance and decision support amongst others.

By reconfiguring the manufacturing systems via the AI-DT model, manufacturing industries will have the opportunity to streamline their operations seamlessly based on demand requirements of market dynamics. The AI-DT integration will enable a more precise manufacturing systems tailored requirements in line with the Just-in-Time principles of Lean manufacturing thereby reducing wastes [20]. While AI can enable predictive analytics, DT can enable diagnostic functions via modeling and simulation of the system. Thus, the integration of these digital technologies can support smart manufacturing industries in the delivery high-quality products. Their synergistic effect could promote system's automation allowing the system to run independently and continuously and independently with less errors or failure as a result of automated controls [20].

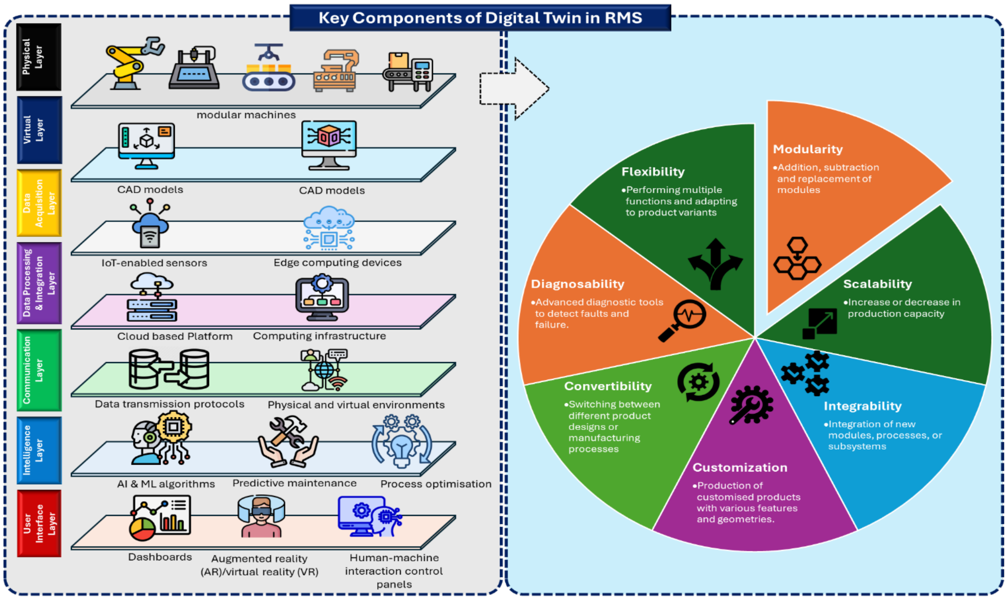

Figure 1: Major components of digital twins in RMS

2.2 Applications of DT in Manufacturing

DT is a virtual imitation, replica, simulation or demonstration of a physical system or process, object or machine that can be used for analysis, monitoring and optimization [21]. The technology is time and cost effective because it can save the time and cost needed for conducting physical experimentation or monitoring of an equipment, process or plant [22–27]. The emergence of computing power and data analytics has made the development of virtual replicas of physical systems possible [23]. DT models vary in functionality, complexity and capability depending on the overall goal or target. It may range from a basic virtual model employed for a simple representation of equipment to a complex model used for monitoring, process analysis and optimization of the production processes. It is a robust tool that can be deployed to visualise and monitor the physical manufacturing plant or process in order to optimise or predict its performance or the need for maintenance [24–26]. It can enhance the product development through all its phases and facilitate predictive maintenance by monitoring equipment performance or failures [25, 26]. DT enables the optimisation of processes and predictive analytics leading to reduction in system's failure and downtime. Through a review of literature on DT in manufacturing, a better understanding of the state-of-the-art can be grasped while gaps can be identified for future studies and improvement.

DT has evolved over the years as a virtual replica of the physical systems or processes and many manufacturing industries have adopted its use for simulation and understudying the performance of machines and process during manufacturing, although the technology is yet to be fully explored. Existing studies have shown the demonstration of DT in intelligent and smart manufacturing geared towards product design, quality inspection, scheduling, production planning, maintenance etc. [28–30].

Liu *et al.* (2024) [31], suggested the use of an innovative reference model termed “DT-based manufacturing system” due to its ability to improve and enhance the accuracy of smart manufacturing system via effective simulation and monitoring. Leng *et al.* (2019) [32], suggested the use of manufacturing cyber-physical system enabled DT for controlling smart factories while Zhang *et al.* (2019) [33], proposed a five-dimensional DT model that can map the physical and virtual twins. Qi and Tao (2018) [34], suggested the integration of big data with DT for effective data access and comparison. Wei *et al.* (2023) [35], suggested the development of a DT enabled manufacturing equipment based on the axiomatic design principle while Lechler *et al.* (2020) [36], proposed a model that can be used to integrate and classify the different areas of DT in manufacturing while Aivaliotis et al. (2019) [37], proposed the use of the DT for predictive maintenance. Touckia *et al.* (2022) [38], used the modeling and simulation technique to investigate the behaviour of RMS aided by the DT. Findings indicates that the DT can enable RMS to achieve scalability, modularity and flexibility. The authors further suggested the integration of ML algorithms into the DT-RMS model for prescriptive analytics.

In the aerospace and automobile industries, DT can be used to simulate behaviour of its components throughout its lifecycle or aircraft or automobile performance to ensure efficiency, safety and sustainability. [38–43]. It can be employed for predictive maintenance to reduce downtime, or breakdowns, thus extending the useful life of aircraft or automobile components [44]. Furthermore, it facilitates access and exchange of real-time information of seamless part production thus reducing the manufacturing lead time [45]. Papadopoulos (2024) [46], proposed a framework for intelligent RMS that employs the capabilities of robotic automation collaborative dual-arm end-effector, and ML algorithms for effective handling operations during manufacturing

Even though the benefits are numerous, the integration of DT with AI has not been sufficiently discussed or harnessed.

2.3 Enablers of DT technologies in manufacturing

DT can enable manufacturers to discover useful critical insights that can promote informed decisions and enhance process performance during manufacturing. The technology is a powerful tool that can enable improved productivity and assist manufacturing industries to stay competitive amidst the increasing market complexity and competitiveness. The technology is gradually being embraced by many manufacturing industries to streamline operations leading to the development of an efficient, agile, more resilient, and responsive production processes. DT as an innovative solution can assist manufacturing industries in the design of systems, process and facilities to achieve decarbonisation, reduction in energy consumption and carbon emissions to maintain an environmentally sustainable practices. DT can monitor carbon footprint, operational efficiency and resource utilisation, to reduce the environmental impact, as the momentum for carbon neutrality continues to intensify globally. Despite the merits and potentials of DT, it can be deployed in manufacturing in isolation as there are other enabling digital technologies that can enhance its capability. These include:

a) *Sensors and Internet of Things (IoT)*: Modern manufacturing are data-driven and DT relies on data for optimal performance, thus, sensors are used for real time data capturing which serves as input into the DT model for simulation via the IoT devices which is used for data transmission in real time.

b) *Artificial Intelligence (AI):* DT models performs well when embedded with AI algorithms for the analysis of data to derive useful predictive insights. This will enable automated decision-making aimed at optimizing the manufacturing process.

c) *Virtual Reality (VR):* VR provides an interactive and immersive learning environment for DT which is necessary for understudying the manufacturing processes, for effective decision making [27]. Thus, The VR technology enables DT-driven simulations, hands-on learning enabling workers to interact and gather experience about the manufacturing processes in a controlled environment. It accelerates the learning curve, promote skills acquisition and knowledge transfer, thereby enhancing the competence and efficiency of workers in the manufacturing set up.

The reviews shows that DT technology plays important roles in facilitating training programmes, human capacity development in the manufacturing environment. It enhances product design and optimization, validation of conceptual ideas, process monitoring and adjustment of process virtually to save the time and cost required for physical prototyping. Many manufacturing industries are yet to fully integrate DT into their manufacturing models while some have integrated it at various levels. Its integration can enable the replication of manufacturing systems virtually and improve resilience in a dynamic environment. The integration requires some hardware and software requirements especially for data acquisition and transmission.

From the above-mentioned, DT can be perceived as technological upgrade that can enhance manufacturing efficiency, agility and flexibility, as well as resource, workforce or process optimization, in smart manufacturing. Some complexity in manufacturing characterised with risks or uncertainness can be addressed via DT in order to achieve the goals of manufacturing. Thus, manufacturers can leverage of the predictive analytics of AI-enabled DT to identify and correct potentials failures [37]. Its capability for predictive maintenance underscores its need for reduction in cost and unplanned downtime during maintenance operations. Touckia et al. (2022) [38], explored the modeling and simulation approach to investigate the behaviour of RMS when aided by DT. The outcome of the study indicates that the DT can enable RMS to meet it reconfigurability requirements such as scalability, modularity and flexibility. Hence, the authors suggested the integration of machine learning algorithms into the DT-RMS framework for prescriptive analytics.

DTs can revolutionize the manufacturing landscape through effective monitoring, predictive maintenance, and optimization of equipment and processes. However, there still exists some challenges and gaps that must to be addressed to fully harness its potentials in smart manufacturing. For instance, studies on the validation, reliability and accuracy of DT models in RMS as well as its integration with AI are scanty.

3. METHODOLOGY

This study demonstrates the development of AI-DT framework for RMS to enable intelligent reconfiguration, adaptive control, continuous monitoring and machine learning (ML)-based predictive analytics. First, systematic literature review was employed to synthesis existing literature on the applications of AI and DT to identify research gaps and foster their integration within the RMS environment. A framework that leverages AI, Internet of Things (IoT) and cloud computing was proposed to process high-volume sensor data was to enable effective system's reconfiguration in real time. Furthermore, a hypothetical case study was utilized focusing on the rail industry to demonstrate the potentials of the proposed system in achieving goals of RMS such as reduction in setup times and enhanced machine utilisation.

This study employs the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) for the selection and analysis of the literature (FIGURE 2). PRISMA offers a robust approach for the synthesis of literature to derive useful information in a transparent manner without bias [47]. The process follows the identification of articles from academic databases followed by the selection of relevant articles based on the inclusion criteria.

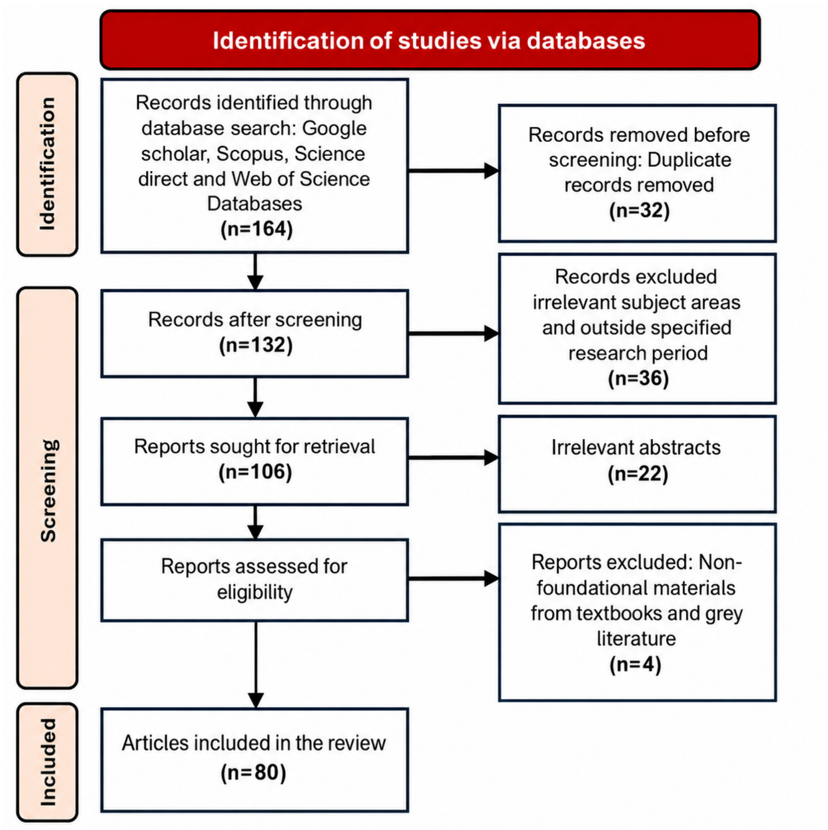

Figure 2: The PRISMA framework for literature analysis and selection

As shown in FIGURE 2, the screening process featured the removal of duplicate articles and exclusion of articles whose focus were not aligned to the study. Finally, 80 peer-reviewed articles with conceptual or theoretical ideals or empirical findings that match with the topic of this study. To minimise biases during the screening process, the authors engaged in brainstorming sessions and collaborative reviews to ensure proper selection of the articles based on defined criteria and to ensure thorough synthesis of the selected articles.

4. RESULTS

4.1 Synthesis of Literature Review

The findings obtained in this study shows that DT has significant contribution and potentials in sustainable manufacturing. It offers benefits such as real-time monitoring and optimization of factors of production, as well as processes, operations, machines, energy and production schedules. It also contributes to effective coordination of supply chain including inventory, logistics and, transportation. In the context of RMS, DT can promote adaptability, agility, flexibility and modularity of RMS so that it will become more responses to market dynamics and forces of demand and supply [48, 50]. Furthermore, DT can be deployed for process investigation and monitoring at the different production stages [51–54].

Hence, manufacturing industries who seek innovative systems that are adaptive, responsive, scalable, and flexible to accommodate the various production needs and market dynamics can embrace DT enabled by AI and other digital technologies for the design and simulation of manufacturing systems, as it is no longer feasible to develop manufacturing that is inflexible or slow in responsiveness to rapid changes in this digital and technologically driven era [55–60]. DT technology continues to evolve with a market worth of 3.1bn USD in 2020, and later 10.1 bn USD in 2023. It is projected to reach 110.1 bn USD in 2028, at a compound annual growth rate of 61.3% from 2023 to 2028 [61]. This indicates the significance of the DT technology and its future prospects.

The outcome of the literature review underscores the significance of DT integration into the RMS. These include enhanced assembly planning, productivity and adaptability, effective failure monitoring and analysis, reduction in wastes, manufacturing time and equipment downtime, and improved overall efficiency.

TABLE 1, presents the overview of some of the find on the use of DT in RMS.

Table 1: Overview of some of the find on the use of DT in manufacturing systems.

S/N	Focus	Findings	Reference
1.	The study focuses on self-adaptive manufacturing with the aid of the DT technology. It employs a modelling framework leveraging on the case-based reasoning technique within modular digital twins to achieve self-adaptive manufacturing.	The study demonstrates the possibility of manufacturing to change and adapt to new situations due to the dynamics of manufacturing and also approach highlights the merits of employing DT for self-adaptive learning purpose. These merits include reduction in manufacturing times, reduction in waste and sustainability via explicit modeling of the domain expertise.	Bolender *et al.* (2021) [62]
2.	It focuses on the development of a loop architecture known as the “Twin-in-the-Loop Architecture” (TiLA).	The performance evaluation indicates that TiLA is suitable for failure monitoring and analysis in the cyber physical production system	Park *et al.* (2019) [63]

continued..

S/N	Focus	Findings	Reference
3.	The study deals with automatic assembly planning by leveraging on DT derived from product description	The outcome of the study showed that manufacturing system could become more versatile with the capability to handle variety of products with little or no reconfiguration effort. The approach also boasts of cost-effectiveness, concurrent product design and assembly planning and explicit product designs.	Sierla *et al.* (2018) [64]
4.	The study deals with the application of DT to support automatic reconfiguration in smart manufacturing.	The performance evaluation of the developed prototype showed improved operational efficiency for reconfiguring production activities with increased flexibility with 29% reduction in reconfiguration time	Zhang *et al.* (2021) [65]
5.	Application of digital twins for enhancing production line in the automotive industry	The outcome of the study indicates that the application of the DT technology brought about a 6.01% increase in the efficiency of commercial production line efficiency with 87.56% profit due to reduction in equipment downtime	Mendi (2022) [66]
6.	The study encompasses the design and implementation of an integrated cyber physical system and DT for the development of automotive body.	An average predicted performance of 96.83% was achieved for the actual production plan. Furthermore, the system demonstrated capacity for ascertaining whether production can be achieved according to the production plan or not.	Son *et al*. (2021) [67]
7.	Integration of DT into RMS validated via modelling and simulation approach	The system is capable of with intelligent sensing and carrying out simulation functions, which enhance production performance. In addition, the incorporation of artificial intelligence into the RMS-DT framework also enabled predictive and prescriptive analytics in the production system which further promotes flexibility and improved decision making	Kombaya Touckia (2022) [68]
8.	Development of a conceptual modular RMS-DT model aimed at achieving improved responsiveness, flexibility and quick decision making	The system was designed to handle data management such as data acquisition, processing, storage and retrieval in real time with the capacity to make quick and informed decision about the configuration of manufacturing system in response to sudden changes	Benderbal *et al.* (2020) [69]

continued..

S/N	Focus	Findings	Reference
9.	This paper focusses on achieving manufacturing excellence via the integration of DT into the manufacturing system.	The study highlights the potentials of integrating and synchronizing the physical product data and the virtual product data or information. This will enhance the understanding of how a product should be manufactured to the required design specifications and requirements. It will also enable comparative analysis of the actual and simulated products in real time in order to adjust the manufacturing processes to meet the targeted product specifications	Grieves (2014) [70]
10.	The study proposes a DT driven technique for achieving quick reconfiguration of manufacturing system. The system consists of two parts namely the semi-physical simulation or data mapping and providing the input data to the second part which conducts the optimisation.	The proposed system is effective in improving the performance of manufacturing system with reduction in the he overheads of the reconfiguration process via automation and optimization processes	Leng et al. (2020) [71]

FIGURE 3, shows that DT is widely applied in the manufacturing sector accounting for 39% of the total application of DT in critical sectors followed by smart city (25%) [72]. This is due to its ability to enhance manufacturing performance via optimised process, quality improvement, cost and manufacturing time reduction.

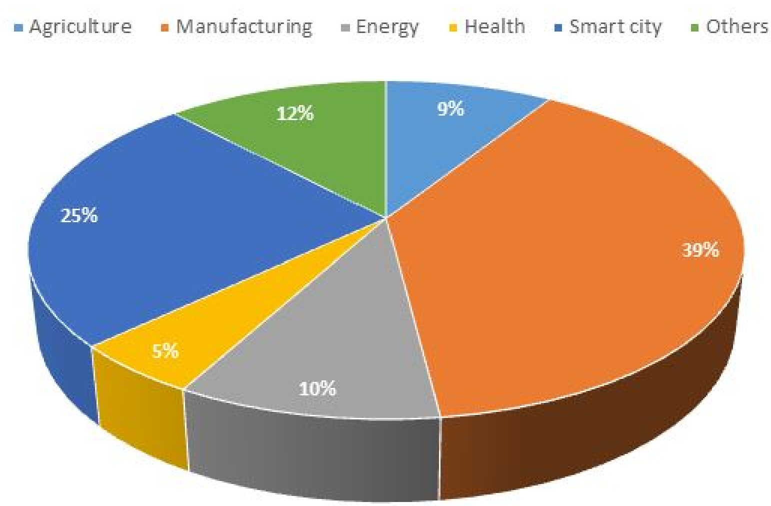

Figure 3: Application areas of DT across various sectors

4.2 AI-DT Framework for RMS

The use of AI in smart manufacturing for demanufacturing operation, diagnostic and predictive maintenance, improving product's functionality and performance and in manufacturing resilience have been reported [73–78]. Therefore, if integrated with the DT model, the potentials of both technologies can be harnessed for a data driven modeling and simulation as well diagnostic and prescriptive analytics. The proposed AI-enabled digital twin is a virtual representation of the physical RMS system that continuously receives real-time data from physical assets with the aid of embedded sensors and processes it using AI algorithms, and provides real time insights or information necessary for autonomous decision making.

FIGURE 4, shows the framework for the integration of AI-DT and other enabling technologies for implementation in the manufacturing environment.

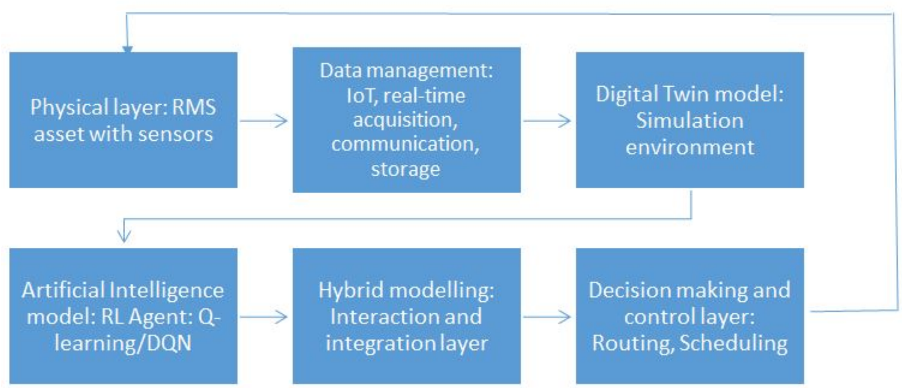

Figure 4: Framework for the integration of AI-DT for manufacturing

As shown in FIGURE 4, the framework comprises of the physical layer having the RMS asset to be monitored It could be a plant, process, equipment, component or system embedded with smart sensors for the measurement of critical parameters physical quantities such as pressure, temperature, vibration etc. The physical layer represents the real-world Manufacturing Environment). This layer will allow the real time data acquisition on the RMS or production status amongst others.

In the second layer which is the data acquisition and communication layer, the acquired data is effectively managed. For instance, the data will be filtered to remove noise, preprocessed to ensure it is represented in a format that is suitable for analysis and securely transmitted via IoT devices. Furthermore, missing values will be handled and the data from multiple or heterogeneous sources will be presented in a unified format. Standard communication protocols such as Message Queue Telemetry Transport (MQTT), 5G, Wide Area Network (WAN) etc. will also be established. Some of the key considerations will include low latency (to ensure rapid data transmission and feedback) as well as data integrity and cybersecurity (to ensure the data set is accurate and not compromised). The third layer id the data management and integration layer comprising of time series data bases and cloud storages where the acquired dataset is stored and through the use of enterprise system such as the Enterprise Resource Planning (ERP), the stored data can be linked to the DT model.

The next layer which is the DT model layer comprises of important analytical and simulation models such as the physics-based Models such as the Computer Aided Design (CAD), Computer Aided Manufacturing (CAM), or Computer Aided Engineering (CAE) models as well as process simulations tools such as the Finite Element Analysis (FEA) and the Discrete Event Simulation (DES) etc. This layer receives transmitted data about the equipment or process and models its virtually using any of the suitable tools mentioned above.

The next layer which is the AI layer is a data-driven model for predictive analytics such as predictive maintenance, defect detection, machine failure or status forecasting or prediction of other features such as energy requirement, production status etc. The AI models also has prescriptive capabilities for providing recommendations on time to failure or optimal process parameters for the improvement of process or product quality. Examples of some suitable AI models that can be embedded in this layer include the machine learning models (such as the decision tree, support vector machine, k-nearest neighbor, random forest, gradient boosting), Deep learning models (such as the neural network, convolutional neural network, recurrent neural network, long short time memory etc.), reinforcement learning model (for adaptive control), natural language processing (for operator interaction) etc.

The AI models have cognitive capabilities in that they have self-learning abilities and can learn from operational data and past decisions to make informed decisions. The next stage called the hybrid modelling, features the combination of physics and ML for higher accuracy. The layer also features the visualization and interaction enabled via the dashboards to monitor key performance indices (KPIs), process trends, real-time machine states. The virtual or augmented realities can be deployed at this stage for the immersive visualization of the DT for remote monitoring. This layer also features human–machine collaboration whereby the operator decision can be supported through real time alerts and simulations outcomes. The last layer which is the decision-making and control layer features a closed-loop control system whereby the outputs from the AI models can be used to configure outputs used to configure or adjust the settings of the RMS automatically to achieve modularity, or scalability etc. The control may also be made in the semi-autonomous mode whereby the operator validates AI recommendations before implementation and the continuous feedback is transmitted into the DT for model refinement and continuous monitoring.

For effective functionality of the proposed framework, cybersecurity through strategies such as data encryption, authentication, access control etc. are necessary. Furthermore, ethical use of AI is recommended to promote explainability and bias reduction. In addition, it is necessary to ensure compliance to regulatory standards such as the ISO 23247 (for Digital Twin in manufacturing) [79], General Data Protection Regulation (for data privacy) [80].

5. VALIDATION OF PROPOSED AI-DT FRAMEWORK

To validate the proposed A-DT framework for RMS, a simulation-based approach was employed due to the limited access to real time or historical manufacturing datasets for RMS. The simulation was designed to mimic an actual manufacturing scenario with consideration for parameters such as stochastic processing times, probabilistic machine failures, and dynamic job arrivals.

TABLE 2, presents the major assumptions underlying the simulation.

Table 2: Major assumptions underlying the simulation

S/N	Assumptions	Description
1.	System configuration	The system assumes a modular RMS with 5 machines in the production line. Each machine can assume three states namely active, idle or filed. The reconfiguration allowed routing changes, scheduling or machine activation
2.	Processing time	The processing time is assumed to be stochastic and uniform ranging from 5-10 minutes
3.	Machine failure	It is modelled to be probabilistic with failure rate ranging from 5-10% per time step while the repair time is random ranging from 5-15 minutes
4.	Demand trend	The demand is assumed to be dynamic and can assume any three scenarios namely: low, medium or high. Thus, the Poisson arrival rate λ is assumed to range between 2-10 job/hour
5.	Reconfiguration activities	The AI agent can perform any of these reconfiguration activities (1) re-route jobs (2) activate backup machines and (3) adjust schedules based on priorities

Equation 1 expresses the reward function (R_f) which penalizes ineffective policy or decision taken by the AI agent and rewards effective policy and decisions.

$$R_f = \alpha T_p - \beta D_t - \gamma R_c \tag{1}$$

Where: T_p is the manufacturing throughput, D_t depicts equipment downtime and R_c represents reconfiguration cost, α is the throughput weight which regulates the priority given to production to maximise the throughput, β is the downtime penalty weight which penalizes machine's idle time or failure to promote faster recovery from failure and effective machine utilization while γ is the discount factor that penalizes frequent or expensive system changes to promote fewer reconfigurations or switching and system stability.

The reinforcement Q-learning equation that relates the reward function to the discount factor is expressed as Equation 2.

$$Q\ (s, a) = R_f + \gamma max_{a^i} Q(s^i,\ a^i) \tag{2}$$

Where $Q\ (s, a)$ represents the action value function which is the expected cumulative reward for taking an effective action (a) in a state (s). The various actions can be 1) re-route jobs (2) activate backup machines and (3) adjust schedules based on priorities while the various states are the current condition of the system which can be machine status (active, idle or failed), queue lengths, demand levels and work-in-progress (WIP).

The architecture of the proposed AI-DT framework is shown in FIGURE 4, consisting of six layers: Physical system (machines and sensors), data management layer (IoT), DT model (virtual environment), and AI model layer (Reinforcement Learning agent), the hybrid modelling, interaction and integration layer where the AI interacts with the DT model to learn optimal reconfiguration strategies and lastly the decision making and control layer comprising of activities such as routing, scheduling or machine activation.

FIGURE 5, shows the model of the five configurable workstations in the production line where dynamic reconfiguration decisions can be determined by the AI model. Each machine can assume three states namely active, idle or filed. The reconfiguration allowed routing changes, scheduling or machine activation.

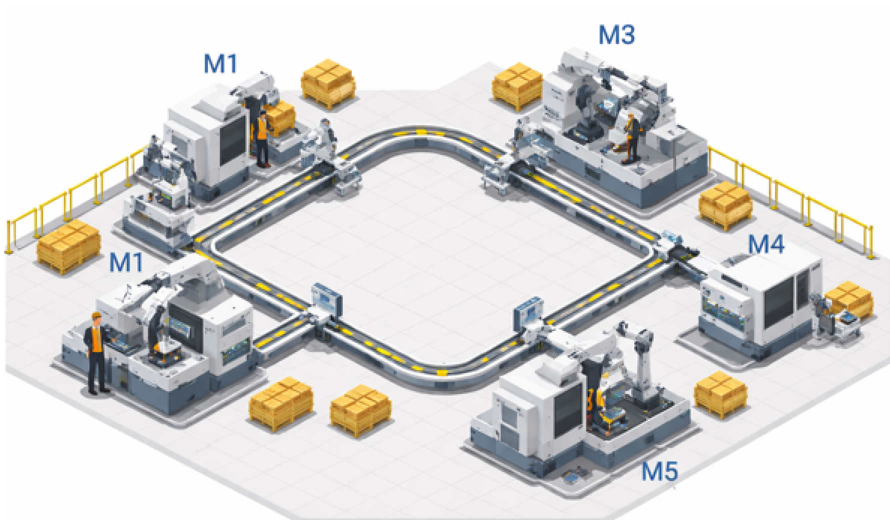

Figure 5: Model of the five configurable workstations in the production line

The performance evaluation of the proposed system was done via simulation implement in the Python environment. The Q-learning agent interacts with the DT environment and training was conducted over multiple episodes where the agent learns optimal reconfiguration policies. For ease of comparison, the baseline model operates without adaptive intelligence. The major performance metrics include (1) system throughput (2) machine utilization and (3) reconfiguration response time under changing manufacturing scenarios such as machine failure or demand fluctuation).

The results indicate that the proposed framework can improve the system's adaptability and reduces downtime compared to baseline configurations. As shown in FIGURE 6, for the intelligent model, the throughput increases steadily as the agent learns optimal decisions for various scenarios while FIGURE 7, shows a significant reduction in the downtime across different manufacturing scenarios indicating effective machine utilization and improved adaptability of the system. The throughput is the number of units produced per time which indicates the system's productivity while the downtime is the time the machines remain idle which indicates the system's inefficiencies. FIGURE 8, shows that the RL agent converges after several episodes, indicating stability. Compared to baseline, the proposed system shows capability for resilience under disruptions. On the overall, the results demonstrate the capability of the proposed AI-DT indicate a steady improvement in throughput, reduction in downtime and improved response time as the AI agent learns optimal policies. Compared to the baseline, the proposed AI-DT model achieved up to 35% increase in throughput and 55% reduction in downtime. Furthermore, the proposed intelligent model achieved 48% improvement in response time (time taken to make changes or reconfigure system in response to manufacturing variations or conditions) compared to the baseline model (FIGURE 8). Hence, the outcome of the validation shows that the proposed system can enable adaptive decision-making under changing manufacturing scenarios with improvement in the system's performance resulting in higher efficiency and reduction in operational losses due to equipment downtime.

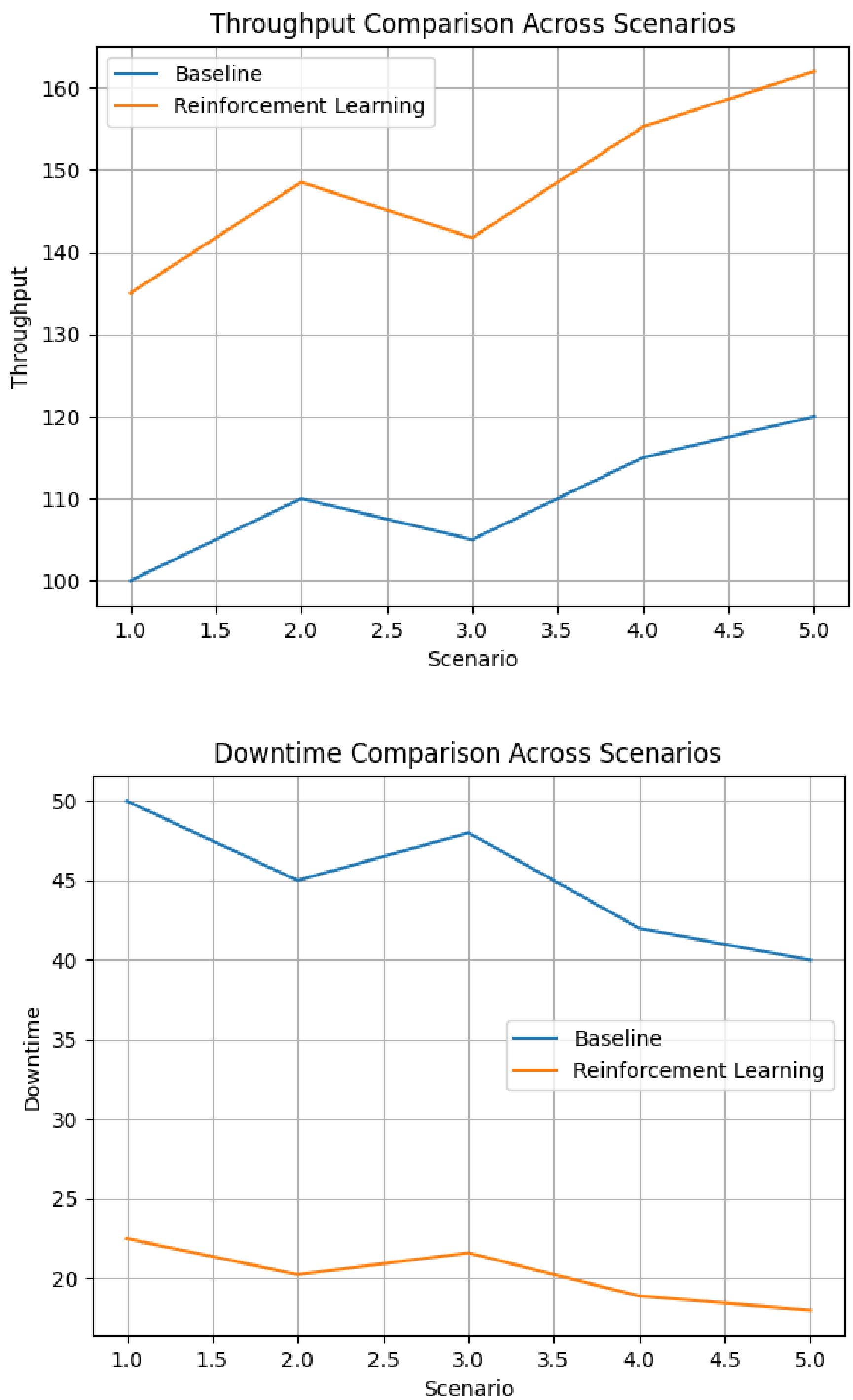

Figure 6: The throughputs and downtime of the baseline and intelligent model for various manufacturing scenarios

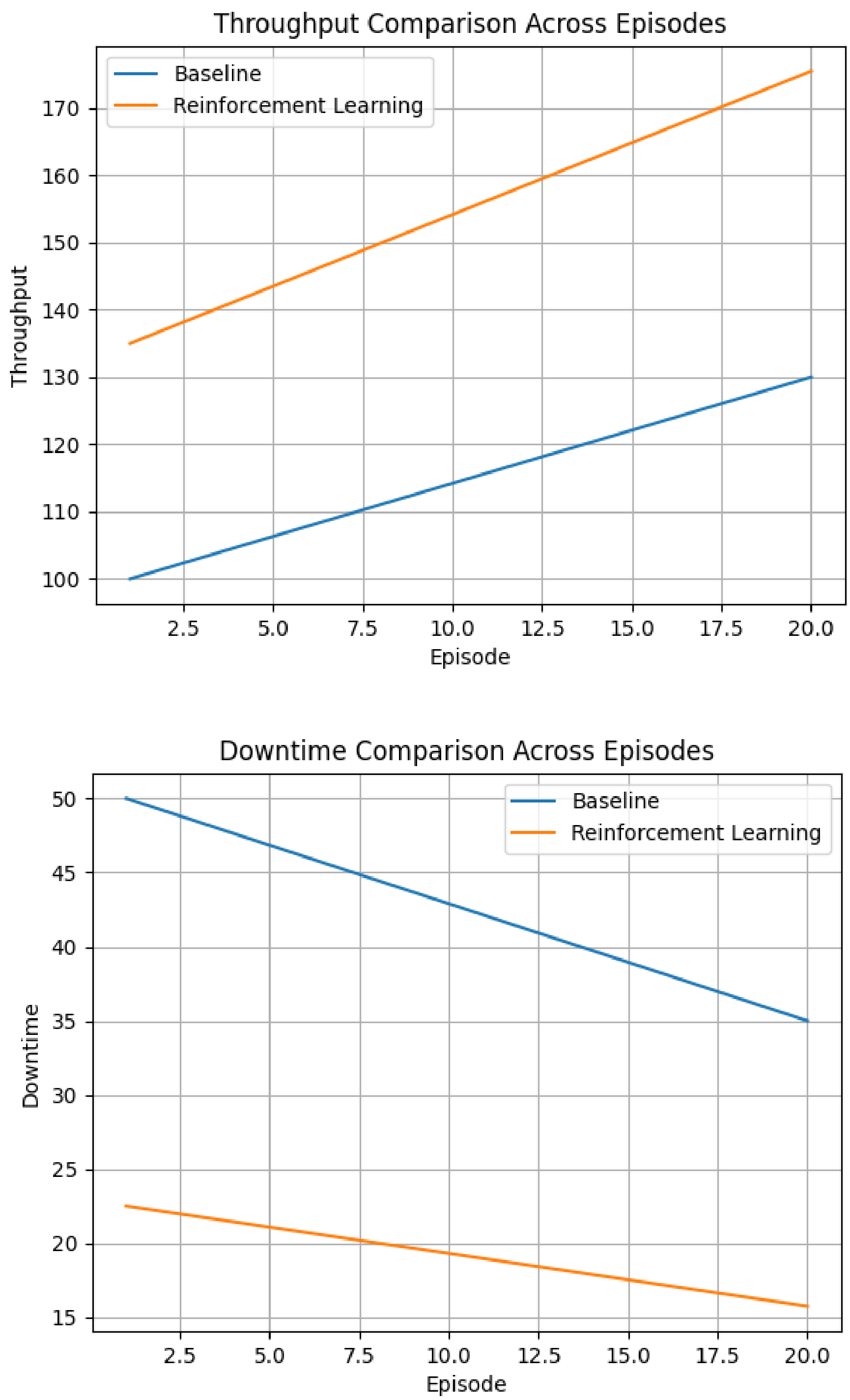

Figure 7: The throughputs and downtime of the baseline and intelligent model for various manufacturing episodes

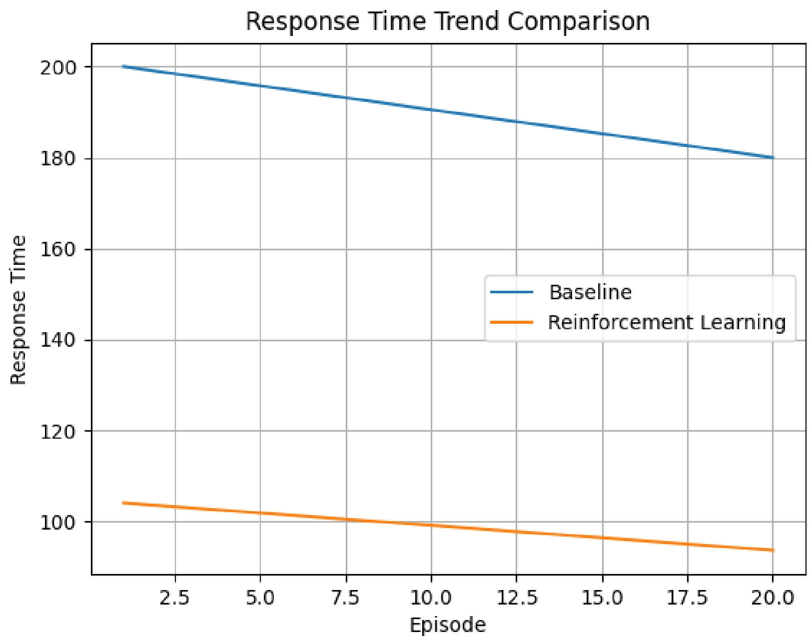

Figure 8: The response of the baseline and intelligent model for various episodes

6. CONCLUSIONS AND RECOMMENDATIONS

This study proposed an AI-DT framework for RMS to enable intelligent reconfiguration, adaptive control, continuous monitoring and machine learning (ML)-based predictive analytics. First, systematic literature review was employed to synthesis existing literature on the applications of AI and DT to identify research gaps and foster their integration within the RMS environment. The outcome of the literature review indicates that, in the context of RMS, DT can promote adaptability, agility, flexibility and modularity of RMS so that it will become more responses to market dynamics and forces of demand and supply. However, there still exists some challenges and gaps that must to be addressed to fully harness its potentials in smart manufacturing. Based on the identified gap, a conceptual framework that leverages AI, Internet of Things (IoT) and cloud computing was proposed to process high-volume sensor data was to enable effective system's reconfiguration in real time was proposed.

Furthermore, an AI-DT framework was developed for effective reconfiguration of the manufacturing system. The validation of the proposed framework conducted in the Python environment indicated that the proposed AI-DT model achieved up to 35% increase throughput and 55% reduction in downtime compared to the baseline model. Furthermore, the proposed intelligent model achieved 48% improvement in response time compared to the baseline.

This study suggests that integrated AI-DT model can significantly promote the agility and resilience of RMS in smart manufacturing. The findings of this study are useful in the exploration of AI-DT models for enhancing the capabilities of the RMS. This study is limited to literature review and development of a conceptual framework. Future studies can consider the validation of the proposed framework via a real-life manufacturing scenario or, a hypothetical case study focusing RMS to demonstrate the potentials of the proposed system in achieving goals of RMS such as reduction in setup times and enhanced machine utilisation.

References

[1] Borjesson FR. A Systematic Qualitative Comparison of Five Approaches to Modularity. In DS 60: Proceedings of DESIGN 2010 the 11th International Design Conference. Dubrovnik, Croatia 2010.

[2] ElMaraghy HA. Flexible and Reconfigurable Manufacturing Systems Paradigms. Int J Flex Manuf Syst. 2006;17:261-276.

[3] Mpofu K, Tlale NS. Multi-Level Decision Making in Reconfigurable Machining Systems Using Fuzzy Logic. J Manuf Syst. 2012;31:103-112.

[4] Koren Y, Shpitalni M. Design of Reconfigurable Manufacturing Systems. J Manuf Syst. 2010;29:130-141.

[5] Daniyan I, Mpofu K, Ramatsetse B, Makinde O. A Framework for a Reconfigurable Welding Jig for Sheet Metal Panel Component of a Railcar. In 2021 IEEE 12th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT).2021:73-80.

[6] Daniyan IA, Dlamini NZ, Sibanda V, Mpofu K. Experimental Validation of a Reconfigurable Guillotine Shear and Bending Press Machine. Cogent Eng. 2023;10:2248743.

[7] Sibanda V, Mpofu K, Daniyan IA, Ale F. Reconfiguration Ramp-up Cost Analysis for a Reconfigurable Guillotine Shear and Bending Press Machine. Cogent Eng. 2022;9:2085002.

[8] Daniyan IA, Adeodu AO, Oladapo BI, Daniyan OL, Ajetomobi OR. Development of a Reconfigurable Fixture for Low Weight Machining Operations. Cogent Eng. 2019;6:1579455.

[9] Murena E, Mpofu K, Ncube AT, Makinde O, Trimble JA, et al. Development and Extraction and Recognition System for Sheet Metal Bending Process Planning Operations. Int J Comput Integr Manuf. 2021;34:598-620.

[10] Ramatsetse BI, Mpofu K, Daniyan IA, Makinde O. Assessment of Reconfigurable Vibrating Screen Technology for the Mining Industries. Ininternational Conference on Flexible Automation and Intelligent Manufacturing. Cham: Springer International Publishing. 2022:79-87.

[11] Kritzinger W, Karner M, Traar G, Henjes J, Sihn W. Digital Twin in Manufacturing: A Categorical Literature Review and Classification. IFAC-PapersOnLine. 2018;51:1016-1022.

[12] Onaji I, Tiwari D, Soulatiantork P, Song B, Tiwari A. Digital Twin in Manufacturing: Conceptual Framework and Case Studies. Int J Comput Integr Manuf. 2022;35:831-858.

[13] Shao G, Helu M. Framework for a Digital Twin in Manufacturing: Scope and Requirements. Manuf Lett. 2020;24:105-107.

[14] Redelinghuys AJ, Basson AH, Kruger K. A Six-Layer Architecture for the Digital Twin: A Manufacturing Case Study Implementation. J Intell Manuf. 2020;31:1383-1402.

[15] Cimino C, Negri E, Fumagalli L. Review of Digital Twin Applications in Manufacturing. Comput Ind. 2019;113:103130.

[16] Gholami H. Artificial Intelligence Techniques for Sustainable Reconfigurable Manufacturing Systems: An Ai-Powered Decision-Making Application Using Large Language Models. Big Data Cogn Comput. 2024;8:152.

[17] Das SK. The Measurement of Flexibility in Manufacturing Systems. Int J Flex Manuf Syst. 1996;8:67-93.

[18] Morgan J, Halton M, Qiao Y, Breslin JG. Industry 4.0 Smart Reconfigurable Manufacturing Systems. J Manuf Syst. 2021;59:481-506.

[19] Koren Y, Heisel U, Jovane F, Moriwaki T, Pritschow G, et al. Reconfigurable Manufacturing Systems. CIRP Ann. 1999;48:527-540.

[20] Mehrabi MG, Ulsoy AG, Koren Y. Reconfigurable Manufacturing Systems and Their Enabling Technologies. Int J Manuf Technol Manag. 2000;1:114-131.

[21] Soori M, Arezoo B, Dastres R. Digital Twin for Smart Manufacturing: A Review. Sustain. Manuf. Serv. Econ. 2023;2:100017.

[22] Borowski PF. Digitization, Digital Twins, Blockchain, and Industry 4.0 as Elements of Management Process in Enterprises in the Energy Sector. Energies. 2021;14:1885.

[23] Zheng P, Sivabalan AS. A Generic Tri-Model-Based Approach for Product-Level Digital Twin Development in a Smart Manufacturing Environment. ROBOT CIM-INT MANUF. 2020;64:101958.

[24] Abburu S, Berre AJ, Jacoby M, Roman D, Stojanovic L, et al. Cognitwin–Hybrid and Cognitive Digital Twins for the Process Industry. IN2020 Ieee International Conference on Engineering, Technology and Innovation. ICE/ITMC. IEEE. 2020:1-8.

[25] Lechler T, Fischer E, Metzner M, Mayr A, Franke J. Virtual Commissioning–Scientific Review and Exploratory Use Cases in Advanced Production Systems. Procedia CIRP. 2019;81:1125-1130.

[26] Mi S, Feng Y, Zheng H, Wang Y, Gao Y, et al. Prediction Maintenance Integrated Decision-Making Approach Supported by Digital Twin-Driven Cooperative Awareness and Interconnection Framework. J Manuf Syst. 2021;58:329-345.

[27] Yildiz E, Møller C, Bilberg A. Demonstration and Evaluation of a Digital Twin-Based Virtual Factory. Int J Adv Manuf Technol. 2021;114:185-203.

[28] Tao F, Cheng J, Qi Q, Zhang M, Zhang H, et al. Digital Twin-Driven Product Design, Manufacturing and Service With Big Data. Int J Adv Manuf Technol. 2018;94:3563-3576.

[29] Can O, Turkmen A. Digital Twin and Manufacturing. Digital Twin Driven Intelligent Systems and Emerging Metaverse. 2023:175-194.

[30] Shao G, Jain S, Laroque C, Lee LH, Lendermann P, et al. Digital Twin for Smart Manufacturing: The Simulation Aspect. In2019 Winter Simulation Conference WSC. IEEE. 2019:2085-2098.

[31] Liu S, Zheng P, Bao J. Digital Twin-Based Manufacturing System: A Survey Based on a Novel Reference Model. J Intell Manuf. 2024;35:2517-2546.

[32] Leng J, Zhang H, Yan D, Liu Q, Chen X, et al. Digital Twin-Driven Manufacturing Cyber-Physical System for Parallel Controlling of Smart Workshop. J Ambient Intell Humaniz Comput. 2019;10:1155-1166.

[33] Zhang C, Xu W, Liu J, Liu Z, Zhou Z, et al. A Reconfigurable Modeling Approach for Digital Twin-Based Manufacturing System. Procedia CIRP. 2019;83:118-125.

[34] Qi Q, Tao F. Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison. IEEE Access. 2018;6:3585-3593.

[35] Wei Y, Hu T, Dong L, Ma S. Digital Twin-Driven Manufacturing Equipment Development. ROBOT CIM-INT MANUF. 2023;83:102557.

[36] Lechler T, Fuchs J, Sjarov M, Brossog M, Selmaier A, et al. Introduction of a Comprehensive Structure Model for the Digital Twin in Manufacturing. In2020 25th IEEE International Conference on Emerging Technologies and Factory Automation. ETFA. IEEE. 2020:1773-1780.

[37] Aivaliotis P, Georgoulias K, Chryssolouris G. The Use of Digital Twin for Predictive Maintenance in Manufacturing. Int J Comput Integr Manuf. 2019;32:1067-1080.

[38] Kombaya Touckia J, Hamani N, Kermad L. Digital Twin Framework for Reconfigurable Manufacturing Systems (Mrss): Design and Simulation. Int J Adv Manuf Tech. 2022;120:5431-5450.

[39] Bachelor G, Brusa E, Ferretto D, Mitschke A. Model-Based Design of Complex Aeronautical Systems Through Digital Twin and Thread Concepts. IEEE Syst J. 2020;14:1568-1579.

[40] Conde J, Munoz-Arcentales A, Romero M, Rojo J, Salvachúa J, et al. Applying Digital Twins for the Management of Information in Turnaround Event Operations in Commercial Airports. Adv Eng Inform. 2022;54:101723.

[41] Zhang X, Zhu W. Application Framework of Digital Twin-Driven Product Smart Manufacturing System: A Case Study of Aeroengine Blade Manufacturing. Int J Adv Robot Syst. 2019;16:1729881419880663.

[42] Piromalis D, Kantaros A. Digital Twins in the Automotive Industry: The Road Toward Physical-Digital Convergence. Appl Syst Innov. 2022;5:65.

[43] Damjanovic-Behrendt V. A Digital Twin-Based Privacy Enhancement Mechanism for the Automotive Industry. In2018 International Conference on Intelligent Systems (IS). IEEE. 2018:272-279.

[44] Cooke P. Image and Reality: ‘Digital Twins’ in Smart Factory Automotive Process Innovation–Critical Issues. Reg Stud. 2021;55:1630-1641.

[45] Toso F, Torchio R, Favato A, Carlet PG, Bolognani S, et al. Digital Twins as Electric Motor Soft-Sensors in the Automotive Industry. In 2021 IEEE International Workshop on Metrology for Automotive (MetroAutomotive). IEEE. 2021:13-18.

[46] Papadopoulos G, Andronas D, Kaliakatsos-Georgopoulos D, Kampourakis E, Kavvathas K, et al. Reconfigurable Manufacturing Systems Through Intelligent Workpiece Handling and Artificial Intelligence. Procedia CIRP. 2024;128:793-798.

[47] Maware C, Muvunzi R, Machingura T, Daniyan IA. Examining the Progress in Additive Manufacturing in Supporting Lean, Green and Sustainable Manufacturing: A Systematic Review. Appl Sci. 2024;14:6041.

[48] Zadnik Z, Cok V, Karakasic M, Kljajin M, Duhovnik J. Modularity Solutions Within a Matrix of Function and Functionality (MFF). Tech Gaz. 2011;18:471-478.

[49] Dorf RC, Kusiak A. Handbook of Design, Manufacturing and Automation. New York: John Wiley. 1994.

[50] Das SK. The Measurement of Flexibility in Manufacturing Systems. Int J Flex Manuf Syst. 1996;8:67-93.

[51] Fameso F, Desai D, Kok S, Newby M, Glaser D. Coupled Explicit-Damping Simulation of Laser Shock Peening on x12cr Steam Turbine Blades. J Phys Conf Ser. IOP Publishing. 2021;1780:012002.

[52] Fameso F, Desai D, Kok S, Armfield D, Newby M. Residual Stress Enhancement by Laser Shock Treatment in Chromium-Alloyed Steam Turbine Blades. Materials. 2022;15:5682.

[53] Daniyan I, Mpofu K, Fameso F, Ale F. Simulation of Kinematic Hardening Model for Carbon Steel AISI 1035 Weld Stress Prediction During the Welding Assembly of a Railcar. Procedia CIRP. 2020;93:520-526.

[54] Daniyan I, Fameso F, Mpofu K, Uchegbu ID. Modelling and Simulation of Surface Roughness During the Turning Operation of Titanium Alloy (Ti6Al4V). In 2022 IEEE 13th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT). IEEE. 2022:176-181.

[55] Galan R, Racero J, Eguia I, Canca D. A Methodology for Facilitating Reconfiguration in Manufacturing: The Move Towards Reconfigurable Manufacturing Systems. Int J Adv Manuf Technol. 2007;33:345-353.

[56] Krishna MB, Jayswal SC. Reconfiguration of Manufacturing Systems. Int J Eng Res Technol. 2012;1:1-5.

[57] Mittal KK, Jain PK. An Overview of Performance Measures in Reconfigurable Manufacturing System. Procedia Eng. 2014;69:1125-1129.

[58] Moghaddam SK, Houshmand M, Fatahi Valilai O. Configuration Design in Scalable Reconfigurable Manufacturing Systems (Rms); A Case of Single-Product Flow Line (SPFL). Int J Prod Res. 2018;56:3932-3954.

[59] Sibanda V, Mpofu K, Trimble J. Methodology for the Design of a Reconfigurable Guillotine Shear and Bending Press Machine (RGS&BPM). J Eng Des Technol. 2021;19:1317-1343.

[60] Makinde OA, Ramatsetse BI, Mpofu K. Review of Vibrating Screen Development Trends: Linking the Past and the Future in Mining Machinery Industries. Int J Miner Process. 2015;145:17-22.

[61] https://www.marketsandmarkets.com/Market-Reports/digitaltwin-market-225269522.html

[62] Bolender T, Bürvenich G, Dalibor M, Rumpe B, Wortmann A. Self-Adaptive Manufacturing With Digital Twins. 2021. ArXiv Preprint: https://arxiv.org/pdf/2103.11941.

[63] Park H, Easwaran A, Andalam S. Tila: Twin-In-The-Loop Architecture for Cyber-Physical Production Systems. In2019 IEEE 37th International Conference on Computer Design (ICCD). IEEE. 2019:82-90.

[64] Sierla S, Kyrki V, Aarnio P, Vyatkin V. Automatic Assembly Planning Based on Digital Product Descriptions. Comput Ind. 2018;97:34-46.

[65] Zhang C, Xu W, Liu J, Liu Z, Zhou Z, et al. Digital Twin-Enabled Reconfigurable Modeling for Smart Manufacturing Systems. Int J Comput Integr Manuf. 2021;34:709-733.

[66] Mendi AF. A Digital Twin Case Study on Automotive Production Line. Sensors. 2022;22:6963.

[67] Son YH, Park KT, Lee D, Jeon SW, Do Noh S. Digital Twin–Based Cyber-Physical System for Automotive Body Production Lines. Int J Adv Manuf Tech. 2021;115:291-310.

[68] Kombaya Touckia J, Hamani N, Kermad L. Digital Twin Framework for Reconfigurable Manufacturing Systems (Rmss): Design and Simulation. Int J Adv Manuf Tech. 2022;120:5431-5450.

[69] Benderbal HH, Yelles-Chaouche AR, Dolgui A. A Digital Twin Modular Framework for Reconfigurable Manufacturing Systems. In the IFIP International Conference on Advances in Production Management Systems. Cham: Springer International Publishing. 2020:493-500.

[70] Grieves M. Digital Twin: Manufacturing Excellence Through Virtual Factory Replication. White paper. 2014;1:1-7.

[71] Leng J, Liu Q, Ye S, Jing J, Wang Y, et al. Digital Twin-Driven Rapid Reconfiguration of the Automated Manufacturing System via an Open Architecture Model. ROBOT CIM-INT MANUF. 2020;63:101895.

[72] https://www.grandviewresearch.com/industry-analysis/digital-twin-market

[73] Daniyan I, Mpofu K, Oyesola M, Ramatsetse B, Adeodu A. Artificial Intelligence for Predictive Maintenance in the Railcar Learning Factories. Procedia Manuf. 2020;45:13-18.

[74] Daniyan IA, Mpofu K, Adeodu AO. Development of a Diagnostic and Prognostic Tool for Predictive Maintenance in the Railcar Industry. Procedia CIRP. 2020;90:109-114.

[75] Daniyan IA, Muvunzi R, Mpofu K. Artificial Intelligence System for Enhancing Product's Performance During Its Life Cycle in a Railcar Industry. Procedia CIRP. 2021;98:482-487.

[76] Phuluwa HS, Daniyan IA, Mpofu K. Implementation of Artificial Neural Network for Demanufacturing Operation in the Rail Industry. In Proceedings of Soft Computing: Theories and Applications. 2022;2023:11-23.

[77] Daniyan IA, Mpofu K, Daniyan OL, Ale F, Dlamini NZ. Design and Simulation of a Novel Digital Technology for Assembly Operations: A Case Study of Railcar Bogie Application. In Soft Computing: Theories and Applications: Proceedings of SoCTA. 2022;2023:539-550.

[78] Ale F, Daniyan IA, Aderoba OA, Adediran AA. An Artificial Intelligence-Based Integrated Framework for Lean and Smart Manufacturing: A Case Study of the Rail Industry. In 2024 International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG). IEEE. 2024:1-10.

[79] Shao G, Frechette S, Srinivasan V. An Analysis of the New Iso 23247 Series of Standards on Digital Twin Framework for Manufacturing. In International Manufacturing Science and Engineering Conference. American Society of Mechanical Engineers. 2023;87240:V002T07A001

[80] https://eur-lex.europa.eu/eli/reg/2016/679/oj/eng